Essays on subjective expectations and mortality trends

Niu, G.

Publication date:
2014

Document Version
Publisher's PDF, also known as Version of record

Essays on Subjective Expectations and Mortality Trends

Essays on Subjective Expectations and Mortality Trends

Proefschrift

ter verkrijging van de graad van doctor aan Tilburg University op gezag van de rector magnificus, prof. dr. Ph. Eijlander, in het openbaar te verdedigen ten overstaan van een door het college voor promoties aangewezen commissie in de Ruth First zaal van de Universiteit op dinsdag 30 september 2014 om 10.15 uur door

Geng Niu

geboren op 2 december 1986 te Jiangsu, China.

Promotores:	prof.dr. Bertrand Melenberg
	prof.dr. Arthur van Soest
Overige Commissieleden:	prof.dr. Rob Alessie
	prof.dr. Ronald Mahieu
	dr. Martin Salm
	dr. Thomas Post

Acknowledgements

This dissertation concludes my three years of work as a PhD researcher at the Tilburg School of Economics and Management. Over the years, I have been fortunate enough to meet many people, without whom this chapter of my life would have been much less enjoyable.

First of all, I would like to thank my two supervisors: Bertrand melenberg and Arthur van Soest. Both of them are very nice people and have guided me through the sometimes difficult research process with their patience and expertise. I started to work under the guidance of Bertrand three years ago for my research master thesis, which was developed into one of our joint papers and got published eventually. At that time Bertrand also helped me obtain the funding for my PhD project. During the three years, Bertrand has been both encouraging and critical to my research. Arthur became my second supervisor in the second year of my PhD phase, when I became interested in one of his research topics. Since then Arthur has provided me with many instructive research insights. Moreover, seeing Arthur many times in the university sports center inspired me to exercise more often.

I am also very gratitude to Rob Alessie, Ronald Mahieu, Martin Salm and Thomas Post for being on my committee, reading my thesis and giving me very useful comments. In addition, I quite enjoyed the professional but friendly atmosphere during the pre-defense of my thesis.

I shall thank especially Martin Salm, Otilia Boldea, and Federica Teppa for their help in my job searching. Martin encouraged me to go to the AEA conference, where

I found my current position. Otilia provided me with lots of useful information for the job market. Federica wrote a crucial reference letter for me and sent the letter promptly to many places.

I am very glad to have many excellent colleges in both the Department of Econometrics & Operations Research and the Department of Finance, from whom I have learned a lot. I should not forget to mention that the secretaries are always very helpful.

There are many friends without whom my memories here would have been much less colorful. I thank all of you for the time we have spent together and the joy you have given me: Yang Zhou, Ran Xing, Hong Li, Zhenzhen Fan, Yun Wang, Jinghua Lei, Ruixin Wang, Bo Zhou, Yan Xu, Yifan Yu, Xu Lang, Di Gong, Kebin Ma, Wendun Wang, Kan Ji, Zongxin Qian, Huaxian Yin, Liping Lu, Manxi Luo , Yuxin Yao, Chen Sun, Lei Shu , Hao Liang , Yiyi Bai, Zhuojiong Gan, Keyan Wang, Jan Kabatek, Cisil Sarisoy, and many others.

Finally, I dedicate this work to my parents in China for their continuing love and support over all the years.

Geng Niu

Nanjing, China

August 2013

Contents

Chapter 1

Introduction

This thesis consists of four chapters on two topics. The first topic, covered in chapter 2, 3, and 4, is about subjective expectations. Economists have long understood that expectations are important determinants of economic decisions. However, expectations are rarely observed. One way to overcome the problem is to elicit beliefs of individuals, or so-called subjective expectations, directly from survey questions. Data on subjective expectations can help us better understand how people form expectations in reality, without imposing restrictions such as rationality or homogeneity. Subjective expectations in many domains are also found to have predictive power for actual decisions, on top of observed socioeconomic and demographic factors. Recent years witnessed an increasing body of literature in measurement and analysis of subjective expectations. See Manski (2004) and Hurd (2009) for excellent overviews. Following this strand of literature, the three chapters study directly measured expectations on two important assets: housing and stock. Home ownership is very high in many countries and housing is typically the largest asset in most households' portfolios. Stock is often the major component of households' financial wealth. Moreover, shocks of both assets are considered to have impacts on households' consumption plans in the literature (Carroll et al., 2011). Chapter 2 investigate how house price expectations are related to macro and micro characteristics. Chapter 3 focuses on stock price expectations. Both chapters are based on panel data analysis of individual expectations at the micro level. Chapter 4 is also about house price expectations, but is from a macroeconomic perspective and relies on time series analysis of aggregate data. The second topic, discussed in Chapter 5, is about mortality trends. Increasing longevity is an important concern for many developed countries. Forecasting future mortality trends is of great interest for demographic projections and pension planning. However, mortality rates are not easy to predict as the whole distribution might change over time, due to so called (systematic) longevity risk. This chapter introduces a mortality forecasting model, which links mortality trends to trends in economic growth, and studies mortality dynamics for six developed countries. The remainder of this introductory chapter presents the main results and implications of each paper.

1.1 House price expectations

In chapter 2, we explore the relationship between house price expectations, local economic conditions, and households' individual characteristics, based on survey data collected between 2009 and 2014. We also estimate the individual- and time-specific subjective probability distributions for five-year-ahead home values. There are several interesting findings. First, at the state level, we find that recent movements in local house prices are positively related to one-year expectations. Meanwhile, people in areas that experienced the most severe housing bust have higher expectations of future home value changes, especially for the long-run. These results suggest that both short-term momentum and long-term mean reversion might play a role in expectations. Second, house price expectations are procyclical. For example, expectations react positively to decreases in state unemployment rates. In addition, expectations are also positively related to individuals' personal economic experiences, even when local economic conditions and unobserved individual effects are controlled for. Third, there is large variation in both the central tendency and the uncertainty of expectations on future home values across individuals. In general, males, higher income families, and higher educated individuals are more optimistic than others. Forth, individuals are overoptimistic about future home values during the recession period, at least ex ante.

1.2 Subjective Expectations in Stock Market

Chapter 3 studies how households' subjective stock return and uncertainty vary across individuals, time, and forecast horizons, using survey data from 2009 to 2011. Stock ownership is rather limited compared to home ownership. However, stock ownership can be an important determinant of retirement wealth, which is gaining increasing attention as households around the developed countries are bearing more responsibility on saving for retirement. Understanding stock market expectations can help better understand and instruct households' portfolio choice decisions. We find that although long-term expectations do not match short-term expectations through simple annualization, expectations at different horizons share several common features. First, stock market expectations distribute unevenly across different socio-economic and demographic groups. Males, wealthier people, people with higher education levels, and people that follow the stock market on average report much more optimistic expectations. Moreover, both short-term and long-term expectations are very persistent over time. This persistence is mainly explained by an unobserved individual effect rather than expectations of the previous period. This implies that some fixed individual traits are crucial to understand individuals' views about the stock market. Future studies can investigate in more details why individuals hold rather fixed level of optimism or pessimism about future stock prices.

1.3 The Dynamics of Households' House Price Expectations

This chapter is also on house price expectations, as in chapter 2. However, we focus on the dynamics of aggregate expectations instead of individual expectations at the micro level. The study follows closely the macroeconomic literature on inflation expectations. In particular, we test whether house price expectations can be explained by the model in Carroll (2003), which states that individuals form macroeconomic expectations by probabilistically absorbing the views of experts, which are spread through the news media. We extend the model by including past home value changes as an additional factor that might influence expectations of future house prices, to capture momentum effects. Based on monthly expectation data from 2007 to 2014, we find that experts' forecasts positively Granger-cause households' house price expectations, but not vice versa. This observation is consistent with the prediction by Carroll's model (Carroll, 2003). Moveover, perceived home value changes are also positively related to future expectations. Besides, high-educated people are more active in absorbing experts' forecasts than low-educated people Above all, the empirical findings partly support Carroll's model. Future research might incorporate more unique features regarding the housing market into models on macroeconomic expectations.

1.4 Trends in Mortality Decrease and Economic Growth

Chapter 4 studies a separate topic, which is forecasting mortality trends. On the one hand, the literature on extrapolative stochastic mortality models mainly focuses on the extrapolation of past mortality trends and summarizes the trends by one or more latent factors. On the other hand, models in health economics literature are often linking mortality dynamics with observable factors. In this paper we combine insights from the two streams of literature. We begin with a comprehensive analysis on the relationship between the latent trend in mortality dynamics and the trend in economic growth represented by GDP. Subsequently, we extend the Lee-Carter model, a famous stochastic mortality model, by introducing GDP as an additional factor next to the latent factor. Based on data from 1950 to 2007 of six OECD countries, we show that our extended model can provide a better fit for future mortality rates. Our model can also generate more interpretable scenarios about future longevity based on the forecast of future economic growth.

Chapter 2

House price expectations

[Based on joint work with Arthur van Soest.]

Abstract Utilizing new survey data collected between 2009 and 2014, this chapter analyzes American households' subjective expectations on future home values. We explore the relationship between house price expectations, local economic conditions, and households' individual characteristics. We examine the heterogeneity in expectations based on panel data models. In particular, we estimate the individual- and time-specific subjective probability distributions for five-year-ahead home values. House price expectations vary significantly over time, and are positively related to past housing returns and perceived economic conditions. There is large variation in both the central tendency and the uncertainty of expectations on future home values across individuals, which is associated with several socio-economic and demographic factors. Comparing expectations and realizations shows that households only partially anticipated the large downward changes in home values in the time period 2009 – 2011.

2.1 Introduction

Housing is the dominant component of wealth for many households, and the housing sector is an important part of the economy. House price expectations are important for the functioning of the housing market and for life cycle decision making of consumers. Still, the literature on measurement and analysis of house price expectations is sparse. Little research has been done on how households vary in their forecasts of price movements, partly due to lack of data. Notable exceptions are the studies by Case and Shiller (Case & Shiller, 1988, Case & Shiller, 2003, and Case et al., 2012), who conducted surveys of home buyers in four metropolitan areas in the US in the year 1988 and annually from 2003 to 2012. However, still very little is known about subjective house price expectations at a national level.

In this paper we analyze households' expectations on house prices elicited from probabilistic questions in a national longitudinal survey from 2009 to 2014. We study the distribution of expectations across individuals, and link subjective expectations to local house price trends, state-level economic indicators, and individual and household characteristics. Furthermore, we elicit the subjective distribution of future home values for each individual at each point in time and analyze how the central tendency and uncertainty of these distributions vary with household, regional, and business cycle characteristics. Finally, we compare expectations with subsequent realizations to examine how well individuals forecast their home values.

This study adds several empirical findings to the literature. At the state level, we find a certain level of momentum in one-year house price expectations: Recent changes in local house prices are positively related to expected changes in the near future. At the same time, there is evidence of mean-reversion in expectations: People in areas that experienced most dramatic house prices declines have higher expectations of future home value changes, especially for the long-run. Movements in general local economic conditions, measured by unemployment rates, are also positively related to expected changes in future home values. In addition, people with higher education levels are more responsive to changes in local house prices and unemployment rates than others, which is consistent with findings in the existing literature that reactions to macroeconomic news are heterogeneous.

At the individual level, expectations are related to current home values and vary across socio-economic groups. Males, higher income families and higher educated individuals are in general more optimistic than others. These associations may also reflect correlations between some socio-economic variables and unobserved individual effects reflecting optimism or pessimism. After controlling for individual fixed effects to capture this, the characteristics that remain statistically and economically significant are related to perceptions of the personal financial situation, so-called "economic sentiment". In addition to the central tendency, we also find substantial heterogeneity in the subjective uncertainty about five-year-ahead home values across individuals and over time. In particular, female and younger respondents are more uncertain about their future home values. Finally, in all specifications, persistent unobserved individual effects account for around 50% of the unobserved variation in house price expectations.

We also compare expectations of future home values to subsequent realizations. Ex post, households appear to have been overoptimistic about future home values at both one-year and five-year horizons during the financial crisis. This can be due to irrational expectations or unanticipated macroeconomic shocks. For one year expectations, macroeconomic shocks are less likely to be the only explanation as the forecast errors were of the same sign in several consecutive years.

From a methodological point of view, our paper exploits the panel feature of the data and controls for fixed unobserved individual effects. This is different from previous studies on subjective expectations which mainly focus on cross-sectional data. Our panel data analysis is better in identifying and measuring the effects that are related to changes in expectations over time for a given individual. Besides, we use two methods to elicit the subjective distribution of future home values based on answers to probabilistic questions. The first method follows the line of thoughts in Dominitz and Manski (1997b) and fits a parametric distribution for each respondent separately. The second approach follows Bellemare et al. (2012) and uses spline interpolation to fit the subjective distribution non-parametrically, with weaker assumptions on the shape of the distribution. Using two different methods provides more robust inference.

Our paper is related to several strands of the literature. First, measurement and analysis of households' beliefs about future outcomes have attracted increasing attention over recent years. The literature has produced a fair amount of empirical findings on how expectations vary across individuals and over time. Examples are studies on survival expectations (Hurd & McGarry, 1995), future income (Dominitz, 2001), work status (Stephens Jr, 2004), inflation (Bruine de Bruin & Manski, 2011), pensions and retirement ages (Bissonnette & Van Soest, 2012), retirement income replacement rates (De Bresser & van Soest, 2013), and returns on financial assets (Dominitz & Manski, 2007). See also Manski (2004) and Hurd (2009) for excellent overviews. Particularly, household's subjective expectations on stock price have been investigated extensively. While participation in the stock market is limited, housing is widely owned and remains the most significant component of non-human wealth for most households. Still, the survey evidence on house price expectations is rare. The studies by Case, Shiller, and Thompson referred to above (e.g. Case & Shiller, 1988, Case & Shiller, 2003, and Case et al., 2012), include only a limited number of recent home buyers in selected geographic areas, while our study is representative of the US population. Moreover, our study controls for local economic factors and a rich set of respondent characteristics, as well as unobserved individual effects. Our paper therefore substantially extends the existing literature on house price expectations.

Second, this article is also related to a line of research that analyzes the segmentation in housing return and risk, especially along the dimensions of property values and income. For example, Kiel and Carson (1990) and Pollakowski et al. (1991) find that both low- and high-value homes appreciate more rapidly than middle-value homes do, whereas Seward et al. (1992) find that high-value homes have higher appreciation rates only during booming periods. In terms of risk, Peng and Thibodeau (2013) find that in the Denver metro area, house price risk is significantly higher for low-income households. While *ex-post* house price returns and risk have been discussed in a number of papers, our paper provides empirical findings on the heterogeneity in the *ex-ante* expected returns and risk along various dimensions.

Third, there has been a growing interest in understanding the formation of house price expectations. It has been found that in many areas households hold extrapolative expectations in the sense of believing that recent changes will continue in the future, but only a few papers provide direct evidence on such extrapolative expectations in housing. Case and Shiller found that expectations of future home values are higher for home buyers in periods and locations with larger house price increases, and the authors conjectured that optimistic expectations are an important force behind house price appreciations during booms (Case & Shiller, 1988 and Case & Shiller, 2003). Using the Michigan Survey of Consumers, Piazzesi and Schneider (2009) also found that the proportion of individuals that expect rising house prices increased along with actual prices during the recent boom. Our paper links expectations of future home values to state-level house price changes in different time periods, showing that recent changes in local house prices are positively associated with short-term expectations, but have very weak impact on long-term expectations. Moreover, we find that people in places that experienced prolonged house price declines actually have higher expectations of future home values. Apart from past house prices, we also found that expectations are positively related to local economic conditions and people's economic well-being, which indicates an association between house price expectations and the business cycle.

Finally, although this is something we do not address directly, the importance of housing as a component of household wealth implies that data on subjective house price expectations have the potential to make a substantial contribution to our understanding of life-cycle decisions. A large literature has documented a substantial impact of house prices on households' intertemporal choices, including, for example, housing demand (Han, 2010), consumption allocation (Campbell & Cocco, 2007 and Browning et al., 2013), portfolio choice (Cocco, 2004 and Yao, 2004), and fertility choice (Lovenheim & Mumford, 2013). Most papers focus on the impacts of realized house price changes. However, expectations of future values are likely to also play an important role, if decisions are made in an intertemporal context. Miller et al. (2011) first tested the impacts of expected future house price changes, proxied by the changes in the volume of home sales , on economic production. They argue that anticipated house price changes affect life time wealth, and thus have a similar economic impact as realized house price changes. Using subjective expectations data avoids assumptions on how expectations are formed. A number of studies have attempted to include subjective expectations data in the analysis of decisions under uncertainty. For example, Delavande (2008) combine data on probabilistic expectations about the realizations of method-related outcomes with observed contraceptive decisions to estimate a model of birth control choice; Armantier et al. (2013) find that subjective inflation expectations help explain individuals' investment choices; Arcidiacono et al. (2012) estimate a model of students' college major choice that incorporates their subjective expectations on future earnings; and Van der Klaauw (2012) uses respondents' expected future occupation to estimate a structural dynamic model of teacher career decisions under uncertainty. Besides, the analysis of housing wealth effects, or models of life-cycle decisions, might take into account the findings in our paper that house price expectations comove strongly with perceptions of economic conditions.

The remainder of the paper is organized as follows. Section 2 describes the data and the survey questions used in our analysis. Section 3 provides descriptive statistics. Section 4 describes the time patterns of expectations. Section 5 studies the heterogeneity in house price expectations at different horizons based on raw probabilistic answers. Section 6 elicits and analyzes the subjective distribution of five-year-ahead home values. Section 7 compares house price expectations with subsequent realizations. Section 8 concludes.

2.2 Data

2.2.1 House price expectations

The data in this paper is mainly from the Rand American Life Panel (referred as ALP hereafter), which is an ongoing online survey of more than 6,000 individuals aged 18 and over.[1] Respondents in ALP are invited to continue to participate in the surveys even if they miss one or more interviews, resulting in an unbalanced panel. In November 2008, ALP began to include a routinely distributed survey entitled "Effects of the Financial Crisis". The financial crisis survey covers a broad range of topics and provides rich background information for each participant. [2] Of particular relevance for this paper are the questions on subjective home value expectations. For home owners, the survey asks expectations of the respondents' own home values. For renters, the questions are about local or national house prices. To maintain comparability, we restrict our analysis to home owners (more than 70% of the sample). There are six questions on expectations of house prices in each wave.[3] The first one asks the percent chance that home value increases by next year. We label it as Pr(H1>100). Asking expectations in "percent chance" format is shown to be a better way to elicit subjective probability distribution of an individual than, for instance, point expectations (Manski, 2004).[4] The other five are about expectations

[1] See https://mmicdata.rand.org/alp/index.php?page=main for details.

[2] See, for example, Hurd and Rohwedder (2011) for early work using this data.

[3] Detailed descriptions of the questions can be found in the appendix.

[4] After March 2011, the sample size was slightly reduced and a random sub-sample was not asked the subjective questions in percentage form but in the "bins and balls" format. See Delavande and Rohwedder (2008) for a discussion of eliciting subjective probabilities in different formats. We do not use there in the current paper.

of the house price in five years. The second question asks the percent chance that home value increases in five years ($Pr(H5 > 100)$). If $Pr(H5 > 100) > 0$, a third question asks the probability that the home value increases by more than 10% in five years ("Pr(H5>110)"). Similarly, if $Pr(H5 > 110) > 0$, a forth question asks the chance that home value increases by more than 20% in five years ($Pr(H5 > 120)$). And there are two questions about the chance that the home value decreases by 10% and more than 20% in five years ($Pr(H5 < 90)$ and $Pr(H5 < 80)$). For every question, if the respondent does not provide a value immediately, a follow-up question asks for the best guess. The first three waves are quarterly. From May 2009 the major part of the survey is implemented on a monthly basis, while every three months a "long survey" with more detailed questions on housing and spending is administered. As house price expectations and house values are mainly asked quarterly, we draw on the 19 quarterly surveys from February 2009 to January 2014.[5]

2.2.2 State-level variables

It is documented in the literature that financial attitudes and expectations are affected by personal experiences (Malmendier & Nagel, 2011 and Nagel, 2012). The housing market is localized and spatially segmented. Local economic experiences might be particular important in shaping people's expectations on housing. The ALP provides the state of residence for each respondent, which enables us to link subjective expectations to a number of state-level economic variables. While there are potentially many local factors can affect people' expectations, considering that we only have state-level variations, we select only a few salient ones based on the literature.

Many empirical studies have found that future house price movements are influ-

[5] There was no data on five-year house price expectations in the second quarter of 2009. Besides, the sample size for the wave in the second quarter of 2013 is unusually small so we do not use data from this wave.

enced by past trends. We use the quarterly state-level house price index from the Office of Federal Housing Enterprise Ovesight (OFHEO) to construct measures of (quarterly) house price growth rates for each state during the sample period.[6]

Local economic conditions are also found to be correlated to actual house price dynamics (Clapp & Giaccotto, 1994), and may have a direct impact on house price expectations (Favara & Song, 2014). We therefore also link expectations to changes in local unemployment rates. Monthly state level unemployment rates are obtained from Bureau of Labor Statistics.[7]

Arizona, California, Florida, and Nevada, the four so-called sand states, are the states which were most hurt in the recent real estate collapse. There has been significant academic and media coverage of the situation in the sand states since the great recession. Expectations in these areas with severe house price cycles may have distinct features. Accordingly, we construct a dummy variable which is one if the respondent lives in one of these four states and zero otherwise.

2.2.3 Measures of individual sentiment

Research in psychology and behavioral economics indicates that economic expectations are related to sentiment or mood (Kaplanski et al., 2013a). Motivated by this observation, we exploit questions that reflect individual sentiment in the survey and examine whether they are related to house price expectations. There are four questions on different aspects of satisfaction: life satisfaction, job satisfaction, total household income satisfaction, and economic situation satisfaction. Every question has a five-point scale from “Very satisfied” to “Very dissatisfied”. We reverse the answers so that higher values indicate higher levels of satisfaction. In addition, two questions ask about the feelings during the past 30 days: “how much of the time have you felt worn out?” and “how much of the time have you been a happy person?”.

[6]See http://www.fhfa.gov/Default.aspx?Page=14 for details of the HPI. We cannot use the S&P/Case-Shiller Home Price Indices since they do not cover all states.

[7]http://www.bls.gov

Both questions have answers on a six-point scale from "All of the time" to "None of the time". We label the former question "Wornout" and the latter "Happiness". Finally, one question asks the change in financial condition: "We are interested in how people are getting along financially these days. Would you say that you are better off or worse off financially than you were a year ago?". Answers are measured on a scale from 1 ("better-off") to 3 ("worse-off"). The variable "Better off financially" is constructed by reversing the scales so that higher scores correspond to better financial conditions.

Based on the individual measures defined above, we construct two composite measures of sentiment. The first one, "economic sentiment", is related to individuals' perceptions of their economic well-being, and consists of job satisfaction, total household income satisfaction, economic situation satisfaction and being better off financially. The second measure, "non-economic sentiment", is composed of life satisfaction, happiness, and wornout.[8]

2.2.4 Other individual-level variables

The ALP provides a large amount of individual background information. We select a number of individual variables that, as suggested in previous studies, may be related to subjective expectations in general, or may affect people's perceptions on housing and the economy. We include age, gender, race, marital status, education, family income, health, house value, and work status. The variable "Age" is based on the birth month and year. "Female", "White", "Marriage", and "Bachelor" are binary variables corresponding to a respondent's gender, race, current marital situation, and education level, respectively. Self-reported health status is measured on a 1 to 5 scale. We reverse the answers so that higher values indicate better health, and label this variable "Health". "Home value" is based on the self-reported house value.

[8]The procedure to construct a certain composite sentiment measure is as follows: First, we divide the score of each individual measure by the maximum possible scale to make it bounded between zero and one. Second, we average individual measures in the same group to make the corresponding composite measure of sentiment.

We also include a group of binary variables that are related to the work status of the respondent ("unemployed", "retired", and "disabled").

The ALP measures annual family income on a categorical 14 point-scale from below \$5,000 to above \$75,000. For those with income more than \$75,000, a follow-up question is asked on a 4-point scale, from \$75,000-\$99,999 to \$200,000 or more. We combine the answers to the two questions and select the mid-point of each interval as our family income measure, with the maximum value of family income set to \$250,000. We then divide this figure by the number of total household members and label the constructed variable "Income per capita".

2.3 Sample selection and descriptive statistics

We exclude observations with missing or inconsistent responses with regard to the individual demographic characteristic variables.[9] We also exclude observations with missing values on all six subjective probability questions. In total, there are around 18,000 person-wave observations with non-missing values on at least one of the six variables on house price expectations, and complete information on the individual characteristics. To remove the impact of possible outliers, we drop observations with the top one percent or bottom one percent self-reported home values. Finally, to guarantee that house price expectations of the same household refer to the same house, we drop the small proportion of home owners who have moved since four months prior to the first wave of our data.[10]

One concern with subjective probability questions is the fraction of 50-50 re-

[9] A small number of individuals report different genders or races across survey waves.

[10] We exclude people whose state of residence changed during the sample period. Besides, from October 2011, in every wave the following question is asked: "Looking back over the period since October 1st, 2008: Have you moved (i.e. changed primary residence) any time since October 1st, 2008?". We drop the observation if the answer is "Yes". In total, around 10% of observations are dropped. We could not exclude those home owners who moved within state between 2009 and 2011 and who only participated in the surveys prior to October 2011. However, given that the annual mobility rate of US home owners is around 0.03 (Head & Lloyd-Ellis, 2012) and that respondents are continuously invited in ALP, the number of such respondents is probably not big enough to affect our analysis.

Table 2.1: Descriptive statistics for expectations and individual specific characteristics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Pr(H1>100)	38.22	28.94	0	100	18010
Pr(H5>100)	54.6	30.95	0	100	17993
Pr(H5>110)	42.71	29.76	0	100	17975
Pr(H5>120)	23.71	23.33	0	100	17942
Pr(H5<90)	19	19.64	0	100	17946
Pr(H5<80)	12.04	16.53	0	100	17919
Female	0.57	0.5	0	1	18021
Age	56.03	12.53	19.5	94.25	17756
White	0.93	0.25	0	1	18021
Married	0.74	0.44	0	1	18021
Home value ($1000)	234.64	205.21	0.2	1300	17845
Income per capita ($1000)	56.72	46.17	0.31	250	17970
Household size	1.83	1.2	1	11	18021
Bachelor	0.47	0.5	0	1	18021
Unemployed	0.04	0.2	0	1	18021
Retired	0.26	0.44	0	1	18021
Disabled	0.04	0.2	0	1	18021
Non-Eco Sentiment	0.68	0.17	0	1	18014
Eco Sentiment	0.57	0.21	0	1	17853

sponses. 50-50 responses might indicate co-called epistemic uncertainty, which is the tendency to choose the middle of a scale as the answer if the question is not understood. The fractions of 50-50 responses range between 6% and 21% in the six questions about house price expectations. Furthermore, for the question Pr(H1>100), a follow-up question is asked after a 50-50 answer, where participants could choose between 'equally likely' and 'unsure'. Almost 70% of the respondents chose 'equally likely'. Thus the fraction of epistemic uncertainty responses seems to be rather small in our sample and we will not accord for epistemic uncertainty in the models that we estimate.

Table 2.1 presents descriptive statistics for the house price expectations and individual characteristics in our main sample. The average subjective probability of an increase in the home value over the next year is 38%, which is far below the subjective probability of a gain in five years (55%). Besides, for five-year expectations, the average subjective probability of an increase above a given threshold is more than twice the probability of the corresponding decrease. The results imply that people on average believe that the house price will increase in the long run, but short-term expectations are more pessimistic. Given the combination of mean and standard variation, disagreement (dispersion) in short-term expectations seems also to be larger than its long-term counterpart. On average, subjective expectations are consistent with the monotonicity of the cumulative distribution in both sides. As we only include home owners, people in our sample are on average wealthier, older, and have higher levels of education compared to the US population.

2.4 Time patterns of house price expectations

Before further analysis, it is instructive to examine the time patterns of house price expectations during the sample period. To do so, we take at each wave the mean values of house price expectations. To check whether the time pattern in ALP is specific to this survey, we also examine average house price expectations in two other surveys during the similar period. The monthly Michigan Survey of Consumers is a nationally representative survey based on approximately 500 telephone interviews with adult U.S. people. The sample has a rotating panel feature. The Michigan survey began to ask the expected house price change over the next year in January 2007 and over the next five years in March 2007. The Fannie Mae National Housing Survey is a monthly survey implemented by Fannie Mae from June 2010. Each month approximately 1,000 telephone interviews with Americans of ages 18 and older are conducted. Every time a different sample is drawn by Random Digit Dialing telephone sampling. The sample represents the general population of the United States. This survey has a question on the expected percentage change in the one-year ahead house price, very similar to the one in the Michigan Survey of Consumers. Detailed wordings of the questions can be found in the appendix.

Time series of house price expectations in different surveys are plotted in figure 2.1. Visual inspection shows that time patterns across surveys are very similar. Moreover, expectations for different horizons show different time series properties: long-term expectations are always higher than short-term expectations and are less volatile along time. This feature is also manifested in different surveys. To sum up, expected one-year housing returns decreased dramatically during the financial crisis, then rose temporally from 2009 to 2010, fell until late 2011, and began to recover afterwards; expected five-year returns kept decreasing until late 2011, when a recovery started. For expectations data of annual-frequency, the temporal increase (only) in short-term house price expectations between 2009 and 2010 is also documented in Case et al. (2012).

The increase in short-term expectations between 2009 and 2010 is found in different surveys, accompanied by a recovery in house prices (as shown in the Case-Shiller 20-City Home Price Index) and a growth in short-term economic confidence.[11] This recovery stopped after 2010. Five-year expectations remained unchanged during this period. Similarly, Case and Shiller found in their annual home buyers survey that home buyers' expected one-year housing returns increased temporarily from 2009 to 2010, but expected ten-year returns did not (Case et al., 2012). They also found that the "home buyer tax credit" created by the American Recovery and Reinvestment Act in February 2009 was often mentioned as the event that the home buyers thought changed the trend in home prices. The tax credit might lure home buyers into the market, and, in combination with other stimulus programs at the beginning of Obama's presidency (from January 20, 2009), created temporal optimism. This optimism in housing market was short-lived however, perhaps because there were no significant changes in underlying fundamentals and long-term expectations. On the other hand, the ongoing recovery of the housing market as well as the economy as a whole since 2012 has been widely discussed in the media. Some people believe that

[11] The time patterns of short-term economic confidence can be examined by looking at relevant questions in the Michigan Survey of Consumers or the Gallup survey.

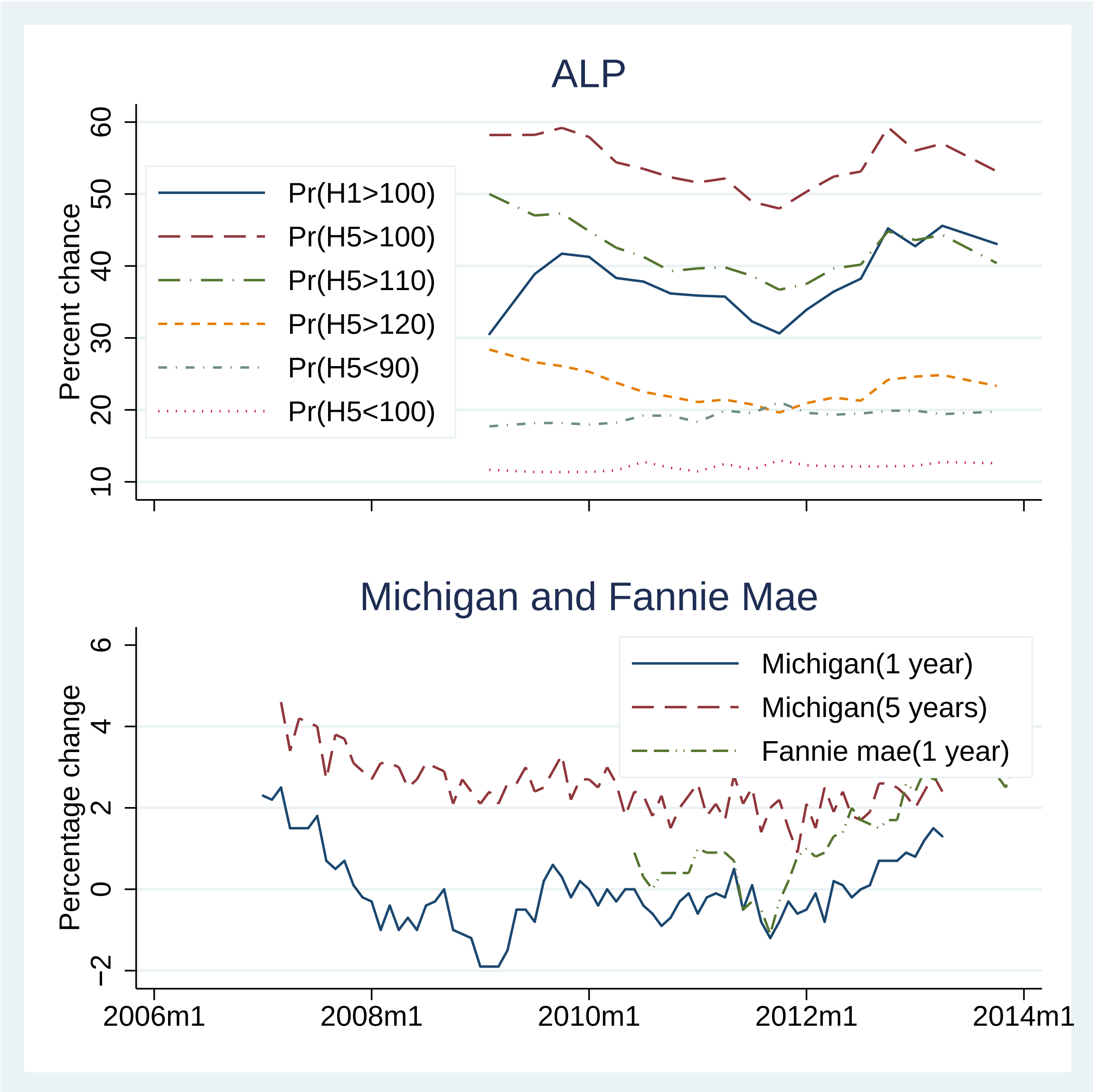


Figure 2.1: Time patters of house price expectations

the recent recovery in housing market is largely driven by the monetary stimulus of the Federal Reserve, while others argue that it is due to the recovery of the economy as a whole. The data in the ALP indicate a recovery in both short-run and long-run expectations.

2.5 Heterogeneity in house price expectations: panel data analysis on probabilistic answers

In this section, we use panel data models to examine the impact of various observable factors on people's short-term and long-term house price expectations. We are mainly interested in the effects of two groups of variables. The first group of variables is related to the state where the respondent resides, as people's perception on housing market may be shaped by their local economic experiences. The second group includes individual demographic characteristics, which are found to be correlated to subjective expectations of different events.

There are six questions on house price expectations in the ALP, we index them $j = 1, 2, \ldots, 6$. Let $p_{j,it}$ denote the answer (percent chance) by individual i at time t for question j. Let k denote the state of residence for individual i. Formally, the specification corresponding to question j is:

$$p_{j,i(k)t} = z'_{k,t}\gamma_j + x'_{it}\beta_j + \tau_j D_t + \alpha_i + \epsilon_{it} \tag{2.5.1}$$

where $z_{k,t}$ is a vector of state-level variables, x_{it} is a group of individual-level variables, D_t is a time dummy, α_i is an unobserved individual effect, and ϵ_{it} is an idiosyncratic error term.

The state-level variables include an indicator of whether the state is one of the sand states, the quarterly percentage change in the unemployment rater, and the quarterly percentage change in the house prices (HPI).[12] Changes in unemployment rates are based on data of the most recent three months before a wave, and changes in the house prices are based on data of the most recent two quarters before a wave. This guarantees that the state-level variables are publicly known before the survey date. The individual variables include the ones summarized in Table 2.1. We take the logarithm of some variables to mitigate the impact of outliers.

We use both Random Effects (RE) and Fixed Effects (FE) models to investigate the relationship between expectations and observed factors. Although the assumptions on unobserved individual effects are stronger, RE models are still helpful to show how expectations vary across different socioeconomic groups. In addition, time variations of many covariates are rather limited in high-frequency surveys, which makes FE models less precise. However, as some of the variables might capture unobserved individual effects in RE models, the coefficients should be interpreted with caution. On the other hand, FE models are able to control for any time-invariant unobserved factors. Table 2.2 show the estimation results for the questions $Pr(H1 > 100)$ and $Pr(H5 > 100)$.[13]

We start from examining the effects of state-level variables. Recent movements in state-level economic conditions are significantly related to one-year expectations only. This indicates that long-term expectations are less affected by temporal economic fluctuations. The effects of changes in unemployment rates are negative as expected, but rather weak. In contrast, recent house price changes have stronger effects. The standard deviation of the state HPI during this period is around 2.5, thus a one standard deviation increase in the quarterly house price growth rate is

[12] The timing of the house price index values does not exactly match the timing of the ALP survey. In estimating the quarterly HPI, all observations within a given quarter are pooled. No distinction is made between transactions occurring in different months within a given quarter. In ALP, the surveys of house price expectations are taken mainly in the beginning of January, April, July, and October. For the January survey, we calculate the most recent growth rates in house prices as the percentage change between the index level in the third and fourth quarters of the previous year. House price growth rates in other quarters are calculated in a similar way.

[13] To save space, we do not report estimation results for the five-year expectations concerning the other thresholds, as the results are similar across the five five-year questions.

followed by approximately a 1 percent point increase in the subjective probability of a gain in one year. These results indicate a certain level momentum effect in short-run house price expectations. At the same time, during the sample period people in sand states on average have higher expectations of future changes in house prices, especially for the long-run. Those people might judge that current house prices are too far below the fundamentals and will recovery in the end. "Momentum" and "mean-reversion" in expectations might coexist if people tend to extrapolate recent house price growth rates for short-term forecast horizons, while rely more on the gap between prices and fundamentals for long-run forecasts. Our empirical results are roughly consistent with this conjecture.

We now turn to the effects of individual-level variables. The effects of individual characteristics vary between expectations at different horizons, but there are some common patterns. People living in houses with higher values are more optimistic about changes in future house prices. Females tend to report lower changes of increases in future home values. For example, the probability that the house price will increase in one year is more than 5 percent points higher for males then for females. This is consistent with the empirical findings that men are more optimistic than women in a broad range of domains (Jacobsen et al., 2014). High income individuals, as well as people with higher level of educations, are also more optimistic. This is in line with findings in a number of subjective financial expectations. See, for example, Dominitz and Manski (2004) and Hurd et al. (2011a). Many of the socio-economics variables are insignificant in the fixed effect specifications, suggesting that they actually capture unobserved heterogeneity rather than causal effects. One exception is household income, which is strongly positive and significant in both RE and FE models. While both non-economic sentiment and economic sentiment are positively related to expectations under the RE specification, only economic sentiment is significant in the FE specification. The magnitudes of sentiment measures are also economically significant. It seems that the economic sentiment index

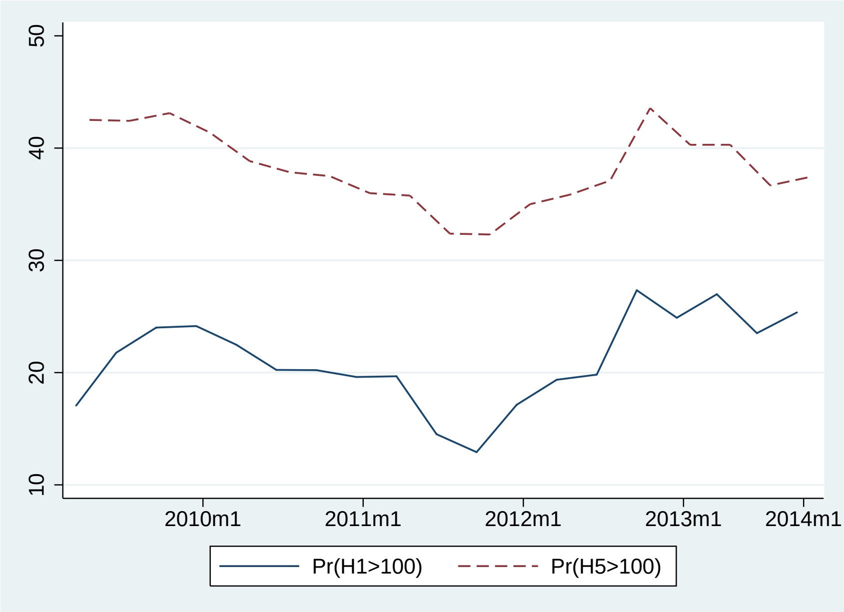


Figure 2.2: Time dummy coefficients from FE specifications in table 2.2

reflects more than merely a mood effect.

The estimate of ρ in the bottom row of the table shows that there is substantial unobserved heterogeneity, in spite of the large number of variables that are controlled for. Around 50% of the overall unexplained variation in the subjective probabilities are captured by unobserved individual effects.

Time dummies are included for all specifications and are jointly significant in all cases.[14] In the models we already control for local economic conditions and economic sentiment, which are expected to capture the impact of general economic conditions. Thus, shocks more specific to the housing market seem to play a role. Figure 2.2 plots the coefficients of time dummy variables for the FE specifications in table 2.2. The time patterns of expectations based on the regression results are similar to the ones using raw data shown in figure 2.1.

To test whether there is heterogeneity in the response to local economic conditions, table 2.3 adds an interaction terms between local economic conditions and an indicator for having bachelor degree.[15] There is indeed a stronger relationship

[14] Many of the time dummies are highly significant individually as well. Results are not reported in the main text but are available on request.

[15] Other covariates are the same as in table 2.2 and corresponding coefficients are not reported.

Table 2.2: Heterogeneity in house price expectations: probabilistic answers

	Pr(H1>100)		Pr(H5>100)	
	RE	FE	RE	FE
Sand states	2.687*		5.315**	
	(1.126)		(1.289)	
Change in unemployment	-4.935+	-4.787+	3.022	2.802
	(2.602)	(2.666)	(2.153)	(2.167)
Change in house prices	0.369*	0.373*	0.061	0.094
	(0.154)	(0.155)	(0.117)	(0.115)
Age	-0.281**		-0.289**	
	(0.035)		(0.046)	
Female	-5.633**		-8.575**	
	(0.995)		(1.182)	
White	-2.039		0.547	
	(1.512)		(1.560)	
Log home value	0.538*	0.158	0.718**	0.260
	(0.252)	(0.259)	(0.251)	(0.265)
Log income per capita	2.838**	2.232*	4.913**	2.657*
	(0.675)	(1.020)	(0.776)	(1.007)
Household size	0.603+	0.709	1.543**	0.986
	(0.312)	(0.620)	(0.384)	(0.659)
Bachelor	3.941**	0.410	8.065**	-5.197
	(1.092)	(4.077)	(1.104)	(4.227)
Married	-0.373	-1.004	-0.095	-1.477
	(1.019)	(1.982)	(1.229)	(2.602)
Unemployed	2.125+	1.955	1.700	1.584
	(1.282)	(1.483)	(1.125)	(1.302)
Retired	0.056	-0.184	1.433	0.767
	(0.873)	(0.998)	(0.971)	(1.130)
Disabled	-0.452	-1.628	1.112	1.682
	(1.508)	(1.336)	(1.356)	(1.486)
Health	0.187	0.215	0.184	-0.308
	(0.405)	(0.483)	(0.416)	(0.501)
Non-Eco Sentiment	4.840*	2.841	5.375**	4.279*
	(2.317)	(2.566)	(1.733)	(1.654)
Eco Sentiment	9.864**	8.390**	8.602**	7.489**
	(1.815)	(2.171)	(1.429)	(1.689)
Constant	29.097**	17.066**	39.596**	42.512**
	(4.149)	(4.806)	(4.390)	(5.071)
Num.Obs	17455	17455	17445	17445
Num.Ind	2029	2029	2029	2029
ρ	0.451	0.524	0.551	0.640
Rej Time dummies = 0 ?	Yes**	Yes**	Yes**	Yes**

Constant term and time dummies are included. Standard errors are clustered at the state level. ρ is the fraction of the unsystematic variation due to unobserved heterogeneity. 'Num.Obs ' is the sample size. 'Num.Ind ' is the number of individuals. Statistical significance is indicated as follows: + p<0.10, * p<0.05, ** p<0.01.

Table 2.3: Education level and response to local economic indicators

	Pr(H1>100)		Pr(H5>100)	
	RE	FE	RE	FE
Change in unemployment	-1.159	-0.924	4.794+	4.842+
	(2.852)	(2.965)	(2.461)	(2.482)
× Bachelor	-9.086**	-9.289**	-4.358	-5.004
	(2.882)	(3.006)	(2.982)	(3.004)
Change in house prices	0.237	0.241	-0.045	-0.022
	(0.150)	(0.150)	(0.142)	(0.143)
× Bachelor	0.288+	0.289	0.229+	0.250+
	(0.169)	(0.175)	(0.124)	(0.127)

Constant term and time dummies are included. Standard errors are clustered at the state level. ρ is the fraction of the unsystematic variation due to unobserved heterogeneity. 'Num.Obs ' is the sample size. 'Num.Ind ' is the number of individuals. Statistical significance is indicated as follows: + p<0.10, * p<0.05, ** p<0.01.

between local economic conditions and one-year house price expectations for people with bachelor degrees. Only college graduates revise their expectations of home value changes upward in response to a decrease in the unemployment rates. Expectations in both the short-run and the long-run are also more responsive to recent movements of local house prices for people with a bachelor degree.

2.6 Modeling subjective distribution of five-year house price expectations

In this section we elicit the subjective probability distributions of future home values, $F_{i,t}(\xi) = Pr_{i,t}(Z \leq \xi)$, of a respondent i at time t. Our inference is based on the answers to J probability questions of the type "what is the percent chance that Z is less (more) than or equal to ξ_j?", where ξ_j-s are the threshold values. As there is only one question about one-year expectations, we constrain our analysis to the five probabilistic beliefs about five-year changes. For these data we have $J = 5$ and $(\xi_1, \ldots, \xi_5) = (0.8, 0.9, 1, 1.1, 1.2)$; see Section 2.1.

With some additional assumptions, the answers to the probability questions can be used to elicit the subjective distribution of each respondent at each time period. We use two approaches for this. The first follows Dominitz and Manski (1997b) and assumes that the subjective distributions all belong to the same parametric family, that of lognormal distributions. The second approach, avoiding this parametric assumption, is the flexible approach developed by Bellemare et al. (2012), based on cubic spline interpolation to get the subjective cumulative densities.

2.6.1 Modeling

The parametric approach

Following Dominitz and Manski (1997b), we assume that an individual answers the probabilistic question on future house prices according to a lognormal distribution, with individual- and time- specific mean and variance. The log-normality assumption is roughly consistent to observed house price dynamics and is used in many papers (e.g. Li & Yao, 2007).

Formally, denote $h_{i,t}$ the house price of individual i at time t, we assume that the subjective distribution of $h_{i,t+5}$ held by respondent i in year t is given by:

$$\ln\left(\frac{h_{i,t+5}}{h_{i,t}}\right) = \mu_{i,t} + \sigma_{i,t}u_{i,t} \tag{2.6.1}$$

where $\mu_{i,t}$ is the subjective expectation of the five years log housing return, $\sigma_{i,t}$ is the subjective standard deviation, and the $u_{i,t}$ are independent standard normally distributed error terms.

At time t the survey asks the probability that the home value of individual i will increase or decrease by a certain percentage over the five years, which gives the subjective probabilities that

$$\frac{h_{i,t+5}}{h_{i,t}} < \xi_j \tag{2.6.2}$$

where $j = 1, \dots, 5$ and $\xi_j = 0.8, 0.9, 1.0, 1.1, 1.2$.

According to our model, the corresponding probabilities are

$$\begin{aligned} Pr_{it}\left(\frac{h_{i,t+5}}{h_{i,t}} < \xi_j\right) &= Pr_{it}\left(\ln\frac{h_{i,t+5}}{h_{i,t}} < \ln\xi_j\right) \\ &= Pr_{it}\left(\mu_{i,t} + z_{i,t} < \ln\xi_j\right) \\ &= \Phi\left(\frac{\ln\xi_j - \mu_{it}}{\sigma_{it}}\right) \end{aligned} \tag{2.6.3}$$

Denoting the answer of individual i at time t to the probabilistic question with threshold ξ_j by p_{jit}, we fit the subjective distribution for each respondent in each wave by nonlinear least squares:

$$\underset{\mu_{it},\sigma_{it}}{\text{Minimize}} \sum_{j=1}^{5}\left(p_{jit} - \Phi\left(\frac{\ln\xi_j - \mu_{it}}{\sigma_{it}}\right)\right)^2 \tag{2.6.4}$$

The flexible approach

Individual i at time t answers J probability questions, giving J points of the subjective distribution function $F_{i,t}(z)$, $(z_1, F_{i,t}(z_1)), \dots, (z_J, F_{i,t}(z_J))$. We can approximate the complete function $F_{i,t}$ using cubic spline interpolation. To be specific, we assume that the function $F_{i,t}(z)$ is given by a polynomial $a_j + b_j z + c_j z^2 + d_j z^3$ on the interval $[z_{j-1}, z_j]$.

The objective is to estimate the $4(J-1)$ interval specific polynomial coefficients in the set $(a_i, b_i, c_i, d_i) : j = 1, \dots J-1$. The estimation is based on $4(J-1)$ equations implied by three groups of restrictions:[16]

1. The distribution function is continuous on its support.

2. The first and second derivatives of $F_{i,t}(\cdot)$ are continuous at the interior thresholds.

3. The boundary conditions: $F''_{i,t}(z_1) = F''_{i,t}(z_J) = 0$.

[16]See Bellemare et al. (2012) for details.

2.6.2 Heterogeneity in subjective distributions of future house prices

To maintain comparability, we exclude a small number of observations (115, less than 1%) in each wave who answered "don't know" to at least one of the five long-term expectation questions. We also exclude observations with "50 percent chance" answers to all five questions. Finally, as some inconsistent probability answers result in implausible distributions (e.g. negative second moment), we add lower and upper bounds to the change in house prices, following the spirit in Bresser and van Soest (2013). Specifically, we assume that the subjective probability of a more than 90 percent decrease in five years is always zero (Pr(H5<10)=0) and that the subjective probability that prices increase by more than 150 percent is also zero (Pr(H5<250)=1).[17]

Table 2.4 shows the estimation results of a model with the same right hand side variables as (2.5.1) and with the elicited subjective median as the dependent variable. The results based on the parametric and flexible approaches are similar, and in line with the results using raw probabilistic answers. Living in one of the sand states is associated with a higher subjective median of the future house price change. Recent changes in state-level economic conditions are not much related to long-run expectations. Turning to the individual-level variables, we find that male and younger respondents and those with higher self-reported home values, higher income, higher education level, or more optimistic perceptions on personal financial conditions have higher subjective medians of the five-year house price change in the RE specifications. In the FE specifications, only the coefficients of economic sentiment variables remain strongly significant. Finally, time dummies are highly significant under all

[17]The bounds are based on historical distributions of five-year house price returns and house price depreciation rates: Five-year nominal housing net returns are in the range $[-55\%, 150\%]$ based on quarterly state-level house price index values from 1975 to 2013, and inflation adjusted net returns are in the range $[-60\%, 110\%]$. We can also take into account the depreciation rate for housing, which can be assumed to be 0.05 annually, as in Iacoviello and Pavan (2013). In any case, the interval $[10\%, 250\%]$ seems to be a reasonably conservative support for the subjective raw returns.

specifications, suggesting a strong influence of nation-wide shocks.

Table 2.5 shows how the subjective interquartile range(IQR), a measure of uncertainty, of the estimated subjective distribution, is related to the same set of explanatory variables. People in the sand states, having experienced dramatic declines in house prices, seem to feel more uncertain about the future house price development. Moreover, females, the elderly, and less educated people have higher uncertainty, which is similar to the findings of subjective uncertainty in stock market expectations (Hurd et al., 2011a and Hudomiet et al., 2011). Finally, the joint significance of the time dummies indicates that subjective uncertainty is also affected by nationwide shocks.

2.7 House price expectations and reported realizations

In this section, we compare expected home value changes with subsequent changes in self-reported home values over the same time-period, which may be interpreted as "realizations," where we use quotes because it should be noted that these self-reported home values are not necessarily identical to objective market values. Still, this comparison is worthwhile to get more insight in the nature of the subjective house price expectations. First, previous studies found that time patterns of self-reported home values and of transaction prices are quite similar (DiPasquale & Somerville, 1995). This is particularly relevant since our analysis focuses on changes rather than levels. Second, perceived house price changes can be more relevant than objective changes if households make decisions based on perceived rather than objective housing wealth. Lastly, self-reported home values are widely used in the literature to measure housing wealth and are the only measure available at the individual level in many cases. Out of the 19 quarterly waves, we can match 15 waves of expectations with corresponding "realizations" of home value changes in

Table 2.4: Heterogeneity in house price expectations: elicited median

	Parametric approach		Flexible approach	
	RE	FE	RE	FE
Sand states	0.031**		0.043**	
	(0.007)		(0.009)	
Change in unemployment	0.001	-0.000	-0.004	-0.005
	(0.013)	(0.013)	(0.018)	(0.019)
Change in house prices	0.000	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Age	-0.001**		-0.001**	
	(0.000)		(0.000)	
Female	-0.019**		-0.010+	
	(0.005)		(0.006)	
White	0.000		-0.012	
	(0.009)		(0.011)	
Log home value	0.002	-0.001	0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)
Log income per capita	0.015**	0.006	0.013**	0.002
	(0.003)	(0.005)	(0.005)	(0.008)
Household size	0.002	-0.002	0.002	-0.000
	(0.002)	(0.003)	(0.003)	(0.004)
Bachelor	0.029**	-0.027	0.020**	-0.042
	(0.003)	(0.027)	(0.005)	(0.039)
Married	0.001	-0.008	0.005	-0.011
	(0.005)	(0.010)	(0.006)	(0.010)
Unemployed	0.006	0.004	0.008	0.004
	(0.005)	(0.007)	(0.007)	(0.010)
Retired	0.004	0.001	0.008	0.006
	(0.005)	(0.005)	(0.006)	(0.007)
Disabled	0.014	0.016	0.023	0.016
	(0.009)	(0.012)	(0.016)	(0.020)
Health	-0.000	-0.003	0.003	0.003
	(0.002)	(0.003)	(0.003)	(0.004)
Non-Eco Sentiment	0.015	0.003	0.019	0.008
	(0.011)	(0.010)	(0.015)	(0.016)
Eco Sentiment	0.043**	0.041**	0.037**	0.042**
	(0.007)	(0.008)	(0.011)	(0.012)
Constant	1.019**	1.079**	1.081**	1.128**
	(0.018)	(0.025)	(0.032)	(0.048)
Num.Obs	16774	16774	16774	16774
Num.Ind	2017	2017	2017	2017
ρ	0.478	0.570	0.402	0.496
Rej Time dummies = 0 ?	Yes**	Yes**	Yes**	Yes**

Constant term and time dummies are included. Standard errors are clustered at the state level. ρ is the fraction of the unsystematic variation due to unobserved heterogeneity. 'Num.Obs ' is the sample size. 'Num.Ind ' is the number of individuals. Statistical significance is indicated as follows: + p<0.10, * p<0.05, ** p<0.01.

Table 2.5: Heterogeneity in house price expectations: elicited IQR

	Parametric approach		Flexible approach	
	RE	FE	RE	FE
Sand states	0.039**		0.034**	
	(0.009)		(0.013)	
Change in unemployment	-0.033	-0.029	-0.069*	-0.061+
	(0.026)	(0.027)	(0.033)	(0.034)
Change in house prices	0.000	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Age	-0.002**		-0.002**	
	(0.000)		(0.001)	
Female	0.019*		0.034**	
	(0.009)		(0.009)	
White	-0.017		-0.028*	
	(0.014)		(0.013)	
Log home value	0.001	-0.000	-0.004*	-0.005*
	(0.002)	(0.002)	(0.002)	(0.002)
Log income per capita	-0.000	-0.004	-0.008	0.001
	(0.007)	(0.010)	(0.007)	(0.011)
Household size	0.002	-0.001	0.001	0.009
	(0.004)	(0.006)	(0.005)	(0.007)
Bachelor	-0.009	0.042	-0.021*	0.066
	(0.006)	(0.051)	(0.010)	(0.072)
Married	0.016+	0.019	0.014	0.009
	(0.009)	(0.016)	(0.010)	(0.020)
Unemployed	0.023+	0.016	0.009	0.001
	(0.013)	(0.012)	(0.012)	(0.014)
Retired	0.003	0.013	0.001	0.011
	(0.009)	(0.009)	(0.008)	(0.010)
Disabled	0.023	0.038*	0.036+	0.033
	(0.015)	(0.019)	(0.022)	(0.030)
Health	-0.001	0.002	0.001	0.007
	(0.003)	(0.004)	(0.005)	(0.007)
Non-Eco Sentiment	-0.001	0.003	-0.011	-0.005
	(0.017)	(0.018)	(0.020)	(0.023)
Eco Sentiment	0.006	0.019	0.016	0.027
	(0.014)	(0.015)	(0.019)	(0.021)
Constant	0.365**	0.240**	0.492**	0.269**
	(0.042)	(0.054)	(0.054)	(0.069)
Num.Obs	16769	16769	16769	16769
Num.Ind	2017	2017	2017	2017
ρ	0.417	0.494	0.351	0.449
Rej Time dummies = 0 ?	Yes**	Yes**	Yes**	Yes**

Constant term and time dummies are included. Standard errors are clustered at the state level. ρ is the fraction of the unsystematic variation due to unobserved heterogeneity. 'Num.Obs ' is the sample size. 'Num.Ind ' is the number of individuals. Statistical significance is indicated as follows: + p<0.10, * p<0.05, ** p<0.01.

one year, and one wave with "realizations" of home value changes in five years.

2.7.1 Comparing expectations and "realizations" using raw probabilistic answers

If the unpredictable part of the realizations of future home values are independent across respondents (implying the absence of aggregate shocks), then under rational expectations, the average subjective probabilities should closely resemble the corresponding fractions of "realizations".[18] Figure 2.3 plots the differences between the average subjective probabilities that home values will increase over the next year and the (corresponding) fraction of respondents whose self-reported home value has increased over the same time period. The figure shows that expectations were consistently more positive than realizations during and shortly after the recession period, and converged in more recent waves. In the period 2009-2011, subjective expectations were much better than the corresponding realizations. For example, in January 2010 the average subjective probability of a gain in home value over the next year is 40%, but the reported home value one year later was larger than the home value reported in January 2010 for only 25 percent of the sample. This implies that *ex post*, respondents were too optimistic in January 2010. Perhaps they did not have rational expectations, but it could also be that a nation-wide shock that could not be anticipated reduced home values. We do not fully disentangle these two explanations for the difference. However, even if negative shocks might be correlated during a recession, rational expectations should have taken this into account. The fact that the difference has the same sign in several consecutive years suggests the former explanation (non-rational expectations) is more likely than the latter (several unanticipated negative shocks in a row). Besides, a Newey-West test controlling for serial correlations up to one year rejects the null that the systematic

[18] In a similar way, Dominitz and Manski (1997a) and Manski (2004) compare expectations and realizations of health insurance, burglary, and job loss, though they use repeated cross-sectional data with one wave of realizations only.

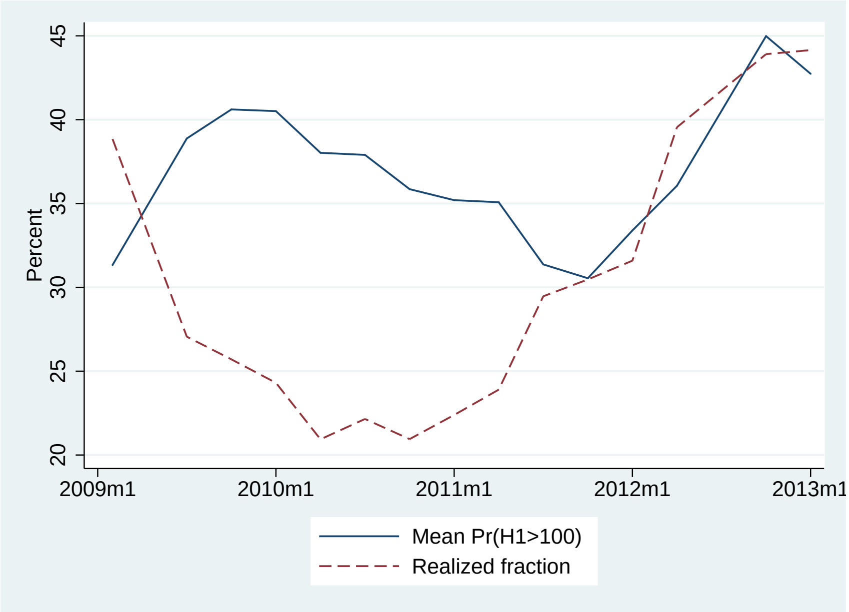


Figure 2.3: One-year house price expectations and "realizations"

Table 2.6: Five-year expectations in Feb 2009 and "realizations" in Jan 2014

	Average subjective probabilities in 2009	Realized fractions in 2014
Pr(H5>100)	0.58	0.39
Pr(H5>110)	0.50	0.24
Pr(H5>120)	0.29	0.14
Pr(H5<90)	0.18	0.30
Pr(H5<80)	0.11	0.18

part of the difference is zero.

Table 2.6 compares expectations and "realizations" over the five year period January 2009 - January 2014. It shows that the average subjective probabilities that home values in five years will increase, increase by more than 10%, increase by more than 20%, decrease by less than 10%, or decrease by less than 20%, are all much larger than the corresponding realized fractions of respondents reporting an increase in the value of their home, an increase by more than 10%, etc. Again, this suggests that realizations over the complete five year-period were worse than expected. Many people did not anticipate the negative influence of the crisis on the values of their home.

The above results imply that households are in general too optimistic about changes in future home values during and shortly after the financial crisis. While it is difficult to pin down the exact reasons behind this overoptimism, we note that similar patterns are found in pervious works concerning other financial expectations of households. For example, Souleles (2004) found that individuals in the Michigan survey were repeatedly negatively surprised by recessions, in the sense that realizations of financial position, business condition, and income were systematically worse than expected around recessions.

2.7.2 Comparing expectations and "realizations" using elicited distributions

We can further investigate the relationship between expectations and realizations by using the entire subjective probability distribution of five-year expectations, along the lines of thought in Dominitz (1998) who examined earnings expectations and realizations. Around 1500 individuals reported home values and five-year house price expectations in February 2009. We base our analysis on the 653 among these who also reported home values in January 2014.

To obtain Table 2.7, we use the estimated 0.25, 0.50 and 0.75 quantiles of each respondent's subjective distribution, using the parametric as well as the flexible estimator from Section 2.6. We then compute for how many respondents the "realized" changes in the reported home values are below each given quantile. Under the joint hypothesis that expectations are rational, that there are no common shocks, and that the sample for which we can do these calculations is not selective with respect to expectations or reported realizations, approximately 25% of the respondents should have a "realization" below their subjective 25% quantile, approximately 50% should have a "realization" below their subjective median, and approximately 75% should have a "realization" below their 75% quantile. The numbers in the table show that this is not the case, particularly for the 0.25 quantile. About half of the respondents report an increase in home value below their subjective 25% quantile, suggesting that many respondents underestimated the chances of a negative outcome, that is, a substantial decrease of the value of their home over the five years period. On the other hand, the fractions of people with a realized change below their subjective 0.75 quantile is close to 75%, suggesting that the respondents anticipated the possibilities of home value increases much better. The results for the median are in between. Assuming that the underlying distribution is Bernoulli, Wald tests also reject the null that the calculated probabilities are not significantly different from the corresponding subjective quantile (0.25, 0.5, or 0.75). Overall, the results confirm that *ex post*, the majority of the respondents were over-optimistic, in line with what we saw in the previous subsection. As explained before, this may be due to non-rational expectations or to common shocks that could not be anticipated.

To see whether the performance of expectations varies across socio-economic groups, the final columns of the table present the same fractions separately for the subsamples of lower and higher educated respondents, as Dominitz (1998) did for earnings expectations. The outcomes for the two groups are actually very similar. Assuming that the probabilities for the high educated and the low educated people come from two independent Bernoulli distributions, they are not statistically different from each other based on Wald tests. In the previous section we saw that the higher educated have higher subjective medians (the random effects estimates in Table 2.4). The results in Table 2.7 show that this difference is reflected in the "realized" five-year changes so that *ex post*, both groups have been equally over-optimistic.[19]

Figure 2.4 plots the same fractions of respondents whose realized change exceeds their subjective quantiles, but now as a function of the respondents' subjective median home value in 2009, using nonparametric kernel regressions. Again, if people have rational expectations and there are no macroeconomic shocks, we would expect the curves to be roughly constant at 0.25, 0.5, and 0.75, respectively. In contrast,

[19]We have also experimented with separating people by gender and found no significant difference.

Table 2.7: Probability that home values in 2014 ($Pr(HV_{2014})$ do not exceed selected subjective quantiles (q_α)

Subjective Quantile q_α	$Pr(HV_{2014} \leq q_\alpha)$					
	all		No Bachelor		Bachelor	
	Parametric	Flexible	Parametric	Flexible	Parametric	Flexible
0.25	0.48	0.52	0.49	0.52	0.48	0.53
0.50	0.67	0.71	0.66	0.69	0.68	0.73
0.75	0.78	0.80	0.77	0.78	0.80	0.82

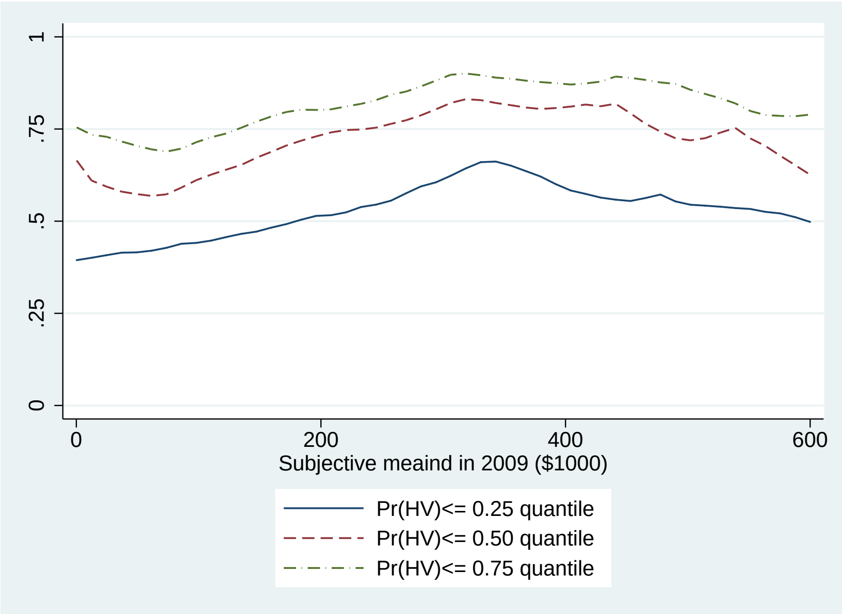
Statistical significance is indicated as follows: + p<0.10, * p<0.05, ** p<0.01.

the estimated conditional probabilities are almost always above the corresponding values, particularly for the 0.25 quantile. This is in line with what we saw in Table 2.7 and suggests that the respondents did not correctly anticipate the downward home value risk over the five-year period. The figure shows that this applies to all groups, irrespective of the anticipated value of their homes in 2014, although the problem is somewhat smaller for owners of houses with very low or very high value than for the intermediate group.

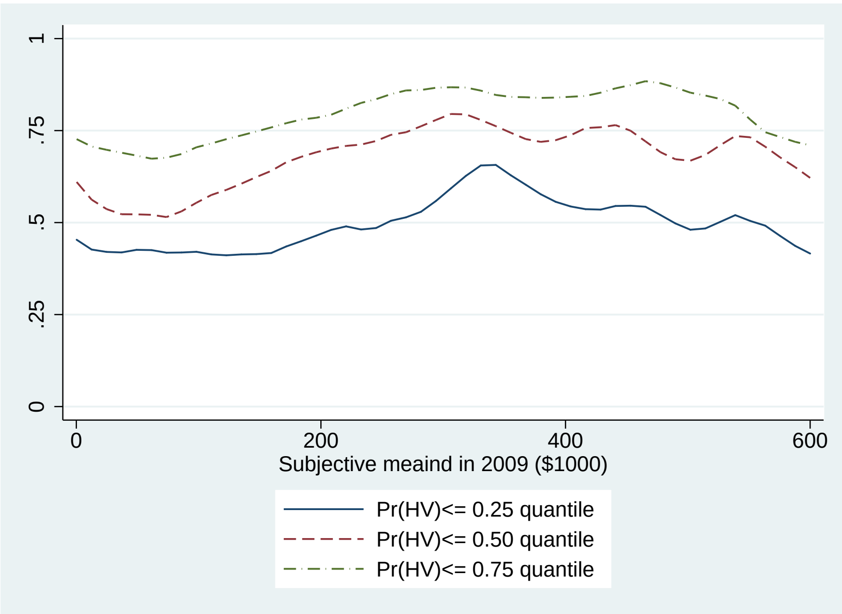
2.8 Conclusion

In this paper we have studied the expectations of US home owners of future changes in the values of their homes. The analysis was based on survey data that directly measure expectations. Our study contributes a number of empirical findings to the literature on subjective expectations in general and on house price expectations in particular.

We have documented a certain level of momentum in short-run house price expectations, but not in the long-run expectations. The long-run expectations seem to be characterized by mean-reversion effects, in that people living in sand states are particularly optimistic about five-year ahead home values. Our sample period however covers mainly the bust period. Using data over a longer period, Case et al. (2012) observed that home buyers are more optimistic about long-term house price changes than one-year changes in early 2000s. The mean-reversion effect seems to



(a) Parametric



(b) Flexible

Figure 2.4: Conditional probability that self-reported home values in 2014 (HV) do not exceed 0.25, 0.50, and 0.75 subjective quantiles in 2009

be absent during the boom period. Combing their findings with ours suggests some kind of asymmetry in expectations between the boom and the bust periods. Several facts might be related to these phenomena. Some studies found that house prices show downward rigidity during periods of decline (Gao et al., 2009). It might be the case that house price expectations also have downward rigidity: people are less likely to extrapolate downward trends during price decline than they extrapolate upward trends during price increase. Many people may believe that housing is a good investment in the long run. Alternatively, households might learned a more comprehensive picture of the house price dynamics after the bust and began to realize the potential mean-reversion. This is consistent with the findings in the lab experiment in Beshears et al. (2013), that for a process featured by short-run momentum and long-run mean reversion, individuals are more likely to realize the existence of mean reversion if the mean reversion dynamics unfold faster. Although these conjectures are interesting, we leave the detailed mechanism behind for future research.

Our findings show that house price expectations are strongly procyclical. At the state level, expectations and unemployment rates move oppositely. At the individual level, expectations comove with people's individual economic situations and economic sentiment, even when unobserved individual effects, nationwide shocks, and local economic conditions are controlled for. This indicates that economic expectations are influenced by personal economic experiences, as emphasized in Nagel (2012).

There is substantial heterogeneity across socio-economic groups in terms of both the central tendency and the uncertainty of subjective distributions of house price changes. The heterogeneity may represent the segmented nature of the housing market and the heterogeneity in outlooks of the economy, which deserves further studies. Besides, studies on wealth distributions might also take into account this heterogeneity, as expected changes in asset prices are related to perceived future wealth levels and housing is the dominant asset for most households.

Finally, future theoretical and empirical work may also try to set up a more structural model that explains expectations and fits the data, and may investigate how house price expectations can affect households' decisions on, for example, mortgage borrowing and consumption.

Acknowledgments

For helpful comments and discussions, we thank Rob Alessie, Ronald Mahieu, Bertrand Melenberg, Thomas Post, 'Martin Salm, Federica Teppa, and seminar participants at the Netspar Pension day, Tilburg University, and the MiSoC Workshop on Subjective Expectations and Probabilities in Economics and Psychology in the University of Essex. The first author acknowledges the Netherlands Organization for Scientific Research (NWO) for financial support. The second author acknowledges the National Institute on Aging (NIA) for financial support.

Appendix

2.9 Questions on house price expectations

2.9.1 Rand American Life Panel

If the respondent owns the home in which he lives (answer “yes" to the home ownership question) and is willing to have probability questions, then the following questions are asked in sequence:

Pr(H1>100):

> On a scale from 0 percent to 100 percent where 0 means that you think there is no chance and 100 means that you think the event is absolutely sure to happen, what do you think are the chances that by next year at this time your home will be worth more than it is today?

Pr(H5>100):

> What are the chances that over the next 5 years your home will be worth more than it is today.

Pr(H5>110)(If Pr(H5>100)>0):

> What are the chances that 5 years from now the value of your home will have gone up by more than 10 percent?

Pr(H5>120)(If Pr(H5>110)>0) :

> What are the chances that 5 years from now the value of your home will have gone down by more than 20 percent?

Pr(H5<90)(If Pr(H5>100)<100):

> What are the chances that 5 years from now the value of your home will have gone up by more than 10 percent?

Pr(H5<80)(If Pr(H5>90)<100) :

> What are the chances that 5 years from now the value of your home will have gone down by more than 20 percent?

2.9.2 Michigan Survey of Consumers

From January 2007, the survey started to ask expected percentage chance in house prices. The question on one-year expectation reads:

> **[Michigan one year]** By about what percent do you expect prices of homes like yours in your community to go (up/down), on average, over the next 12 months?

The question on five-year expectation reads:

> **[Michigan five year]** By about what percent per year do you expect prices of homes like yours in your community to go (up/down), on average, over the next 5 years or so?

2.9.3 The Fannie Mae National Housing Survey

This survey has a question on the expected percentage change in house prices, very similar to the one in the Michigan Survey of Consumers, which reads:

> **[Fannie Mae one year]** By about what percent do you think home prices in general will go (up/down) on the average over the next 12 months?

2.10 Determinants of home value changes

As self-reported home values of the respondents are observed, we can also study how home value changes are related to local economic conditions and socio-economic characteristics of the individuals. To be specific, we construct a dummy variable, which is one if the self-report home value of the individual increase after one year and zero otherwise. We take this dummy variable as the dependent variable in a Logit panel data model and include the same group of regressors as in model (2.5.1). Table 2.8 shows the estimation results. The sample size reduces as the panel is not balanced and not every individual's self-reported home value in one year can be tracked. Changes in local house prices are positively related to future changes in self-reported home values, although the coefficient under the FE specification is not statistically significant. Home values of individuals with higher income and higher education levels are more likely to increase. In contrast, people with higher self-reported values at the current period are less likely to report an increase in home values one year later. This could be expected if there are transitory measurement errors in the self-reported home values.

Table 2.8: Logit panel data model: home value increases in one year

	RE	FE
Sand states	0.117	
	(0.088)	
Change in unemployment	0.200	0.044
	(0.379)	(0.414)
Change in house prices	0.032*	0.024
	(0.015)	(0.016)
Age	0.001	
	(0.003)	
Female	0.033	
	(0.064)	
White	0.060	
	(0.129)	
Log home value	-0.534**	-2.311**
	(0.029)	(0.161)
Log income per capita	0.359**	0.054
	(0.053)	(0.127)
Household size	0.181**	-0.108
	(0.036)	(0.085)
Bachelor	0.286**	0.573
	(0.067)	(0.719)
Marriage	0.102	-0.255
	(0.076)	(0.243)
Unemployed	0.073	-0.112
	(0.132)	(0.180)
Retired	0.086	0.076
	(0.081)	(0.131)
Disabled	-0.016	0.335
	(0.160)	(0.328)
Health	0.016	0.001
	(0.039)	(0.065)
Non-Eco Sentiment	-0.392+	-0.560+
	(0.212)	(0.301)
Eco Sentiment	0.139	0.249
	(0.166)	(0.250)
Constant	0.324	
	(0.366)	
Num.Obs	12100	10150
Num.Ind	1728	1144
ρ	0.147	

Constant term and time dummies are included. Standard errors are clustered at the state level. ρ is the fraction of the unsystematic variation due to unobserved heterogeneity. 'Num.Obs ' is the sample size. 'Num.Ind ' is the number of individuals. Statistical significance is indicated as follows: + p<0.10, * p<0.05, ** p<0.01.

Chapter 3

Subjective Expectations in Stock Market

[Based on joint work with Bertrand Melenberg.]

Abstract Using high-frequency survey data, this chapter investigates how households' expected stock return and volatility vary across individuals, time, and forecast horizons. Long-term expectations seem to be more optimistic than short-term expectations. Both short-term and long-term expectations are very persistent over time, and are distributed unevenly across socioeconomic and demographic groups. In particular, economic sentiment is positively related to stock market expectations. Time-invariant unobserved individual effects explain a large fraction of the unexplained variation in expectations, while we do not find that current expectations strongly influence future ones. Finally, an analysis of revisions of expectations suggests that information is interpreted differently across individuals and forecast horizons.

3.1 Introduction

Stock market expectations are important determinants of households' risk taking behavior. However, expectations of private households are often not observable. One approach to overcome the problem is to elicit stock market expectations directly from survey questions. Recent years witnessed an increasing body of literature in this direction, especially after the seminal work by Manski (2004). Using data of the 2004 Health and Retirement Study, Dominitz and Manski (2007) found substantial heterogeneity in expected equity returns in the population, where the expected equity returns are positively related to the probability of stock ownership. Hurd et al. (2011b) found similar results in the Dutch population based on data from the 2004 and 2006 waves of the DNB Dutch household panel. Hudomiet et al. (2011) investigated how the recent financial crisis affected expected returns, uncertainty about returns, and disagreement about expected return in the US population, based on one wave of data in the Health and Retirement Study that was collected between 2008 and 2009. Dominitz and Manski (2011) claimed that individuals form stock market expectations in an intrapersonally stable way, as a large fraction of people in the Michigan survey reported the same or very similar beliefs about future stock returns after six months. Using microdata in the Michigan Survey of Consumers, Amromin and Sharpe (2013) found that subjective expectations of stock returns and risk are strongly positively related to households' perceptions of economic conditions.

This paper analyzes households' stock market expectations after the financial crisis, using a recently introduced longitudinal dataset, based on answers to probabilistic questions. We expand previous studies on this topic in several new directions. First, we study different characteristics in households' subjective distributions of future stock returns (mean and standard deviation) at both short (one-year) and long (ten-year) horizons, while the previous literature mostly focuses on short-term expectations. Many households only own stocks indirectly through retirement accounts. Those who own stocks directly do not tend to rebalance their portfolios frequently. Therefore, long term expectations might be more important for households. Second, while previous studies focus on a cross-sectional analysis, we exploit the panel nature of the dataset. By doing so, we are able to examine how individuals update expectations over time. In particular, we study the magnitude and source of persistence in stock market expectations over time. Third, we study the dynamics of revisions in expectations at different horizons. In a recent paper, Hoffmann and Post (2013) also studied the dynamics of individual investors' subjective stock return and risk beliefs, based on a panel of active individual investors. However, our paper is different from theirs in some important aspects. Most importantly, while Hoffmann and Post (2013) focused on how individual investors' personal stock return and risk experiences explain the variations in subjective one-month stock return expectations, we mainly focus on the dynamic patterns of stock return expectations at different horizons per se. Besides, Hoffmann and Post (2013) use qualitative measures of expectations of return and risk and include only stock traders, while we rely on quantitative measures and use a sample that is representative for the whole US adult population over a longer time period. Thus, the two papers can be regarded as complementary.

We have a the following findings. First, we find that on average long-term expected returns (volatility) are higher (lower) than their short-term counterparts. While some papers also found that expected returns at longer horizons are higher (Amromin and Sharpe (2013)), we provide further empirical results regarding higher moments in the subjective distribution.

Second, as in the previous literature, we also find that there is a substantial amount of heterogeneity in households' stock market expectations, which is related to a number of observed demographic and socio-economic variables. The distribution of expected returns in the population is found to be similar to the patterns found in the previous literature: males, wealthier, higher educated people, and people that follow the stock market tend to report higher expected returns. Furthermore, age is found to be negatively related to expected volatility, which is also documented in the previous literature. However, our sample indicates that higher educated people and people who follow the stock market are more uncertain about future stock returns, which is in the opposite direction of the findings in Hudomiet et al. (2011). Thus, in contrast to expected returns, how expected volatility varies across different groups of people is still not very clear. An additional new finding is that the patterns of heterogeneity in the population regarding stock market expectations are very similar at different horizons.

Third, we find that the subjective distributions of future stock returns are quite persistent both in the short run and in the long run. People tend to report similar values of expected returns and volatility at different time points and their relative ranks in terms of stock market expectations do not change very much over time. We further distinguish the roles of unobserved individual effects and state-dependence by estimating dynamic panel data models. We find that the high persistence is mainly due to unobserved time-invariant individual characteristics, while the impact of state-dependence is quite small. This indicates that most households hold a rather fixed belief on future stock returns and revise this belief only slightly over time.

Forth, apart from the levels of expectations, we also find that households revise expectations in a substantially different way. Moreover, households revise expectations quite differently across horizons. As revisions in expectations are related to how people process new information, and stock market relevant information is mostly publicly available, the results suggest that similar information might be interpreted quite differently across people and across forecast horizons.

The paper is organized as follows. In section 4.3, we describe the data used in this paper and how we measure stock market expectations. In section 3.3, we provide some descriptive analysis of the elicited mean and volatility of households' subjective distributions of future stock returns. In section 3.4 we use static panel data models to study how stock expectations vary across different groups of people. In section

3.5, dynamic panel data models are applied to further study the relationship between expectations at different periods. Section 3.6 studies the dynamics of revisions in expectations at different horizons. Section 3.7 concludes.

3.2 Data

The data is mainly obtained from the Rand American Life Panel (ALP). This panel is an ongoing online survey of a group of more than 6,000 individuals aged 18 and over.[1]

Beginning at November 2008, Rand routinely distributed a survey entitled 'Effects of the Financial Crisis' in the ALP. The financial crisis survey covers a broad range of topics, see Hurd and Rohwedder (2011) for a recent work using this survey. The first three waves are quarterly. From May 2009 on the major part of the survey is implemented at a monthly frequency. The key variables we are interested in are the expectations about stock market returns at a one-year horizon and at a ten-year horizon.

3.2.1 Data on expectations

There are three questions on one year ahead stock market expectations in every wave. The first one asks the percent chance that mutual fund shares will be worth more than they are today by next year. We label it the "$Pr(R1 > 1)$" question. If $Pr(R1 > 1) > 0$, a second question asks the chance that stock price increases by more than 20% by next year. We label it the "$Pr(R1 > 1.2)$" question. Similarly, if $Pr(R1 > 1) < 100\%$, another question asks the chance that stock price decreases by more than 20% by next year. We label it the "$Pr(R1 < 0.8)$" question. Detailed descriptions of the questions can be found in the appendix. There are also three questions on ten year ahead stock market expectations, which are designed in a sim-

[1] The data is publicly accessible at https://mmicdata.rand.org/alp/index.php?page=main

ilar way as in the one year expectations. We label the three long-term expectations as "$Pr(R10 > 1)$", "$Pr(R10 > 1.2)$", and "$Pr(R10 < 0.8)$", respectively.

The attrition rate is low in this survey. However, after March, 2011, the sample size was reduced as a random sub-sample was not asked the subjective questions in percentage form anymore. Instead, they were asked to express expectations by allocating balls into different bins. To maintain a more balanced panel, we focus on the data up to March, 2011. In addition, while the questions $Pr(R1 > 1)$, $Pr(R1 > 1.2)$, $Pr(R1 < 0.8)$, and $Pr(R10 > 1)$ are asked monthly, the questions $Pr(R10 > 1.2)$ and $Pr(R10 < 0.8)$ are asked every three months. To make expectations of different horizons comparable, we only include waves that have observations for all six probabilistic questions, which results in nine waves of (roughly) quarterly data from February 2009 to March 2011.[2]

3.2.2 Data on individual characteristics

The surveys in the ALP also provide a large amount of individual demographic and socio-economic variables. We focus on a number of individual variables that might be related to stock market expectations as suggested in the previous literature. These variables include age, gender, race, education, family income, health, and work status. "Female", "White", and "Bachelor" are dummy variables corresponding to a respondent's gender, race, and education attainment, respectively. Self-reported health status is measured on a 1 to 5 scale from "Excellent" to "Poor". We reverse the answers so that higher values indicate a better health status, and name this variable "Health". The ALP records annual household income on a 1 to 14 scale from below $5,000 to above $75,000. For those with income more than $75,000, an additional question is asked to code income on a 1 to 4 scale from the range $75,000-$99,999 to the range $200,000 or more. We combine answers in the two questions and choose the middle point of each interval as our family income measure. The upper bound

[2] There is no observation between February 2009 and July 2009.

of family income is set to be equal to $250,000. We label this variable "Household income". We further divide "Household income" by the total number of people in a household to construct a variable with the label "Income per capita", which is mainly used in our analysis.[3]

The literature on psychology and behavioral economics suggests that expectations on economic variables are related to sentiment or mood (Kaplanski et al. (2013b)). Therefore, we also investigate whether individual sentiment is related to stock market expectations at different horizons based on various sentiment measures in the survey. The questions we consider as measures of sentiment include four questions about different aspects of satisfaction ("Life satisfaction", "Job satisfaction", "Total household income satisfaction", and "Economic situation satisfaction"), one question about changes in household financial conditions over a year ("Better off financially"), one question about feeling happiness ("Happiness"), and one question about feeling worn out ("Wornout"). Satisfaction levels are measured on a five-point scale from 1 ("Very satisfied") to 5 ("Very dissatisfied"). Changes in household financial conditions are measured as either 1 ("Better off") , 2 ("About the same"), or 3 ("Worse off"). Questions on happiness and wornout are both about feeling during the past 30 days and are measured on a six-point scale from 1 ("All of the time") to 6 ("None of the time"). Furthermore, we combine responses to the questions "Job satisfaction", "Total household income satisfaction", and "Better off financially" to construct a variable labeled as "Economic sentiment". Similarly, we combine responses to the questions "Life satisfaction", "Happiness", and "Wornout" to construct a variable labeled as "Non-economic sentiment". The procedure is as follows. If necessary, we first reverse the measures of individual questions so that higher values indicate better situations. Then we divide the measure corresponding to each individual question by the maximum possible scale. Finally, we average the answers to each question in a group. The resulting measures of "Economic sentiment" and

[3] The empirical results in the paper barely change if we use the variable "Household income" instead.

"Non-economic sentiment" both lie in between zero and one.

3.2.3 Eliciting expected mean and volatility

As we have observations of different points on the distribution of individual's subjective stock expectations, we can elicit individuals' subjective distributions of future stock prices. In the literature currently there are mainly two ways to make inference on subjective distributions of respondents using probabilistic questions. The first way is to elicit the individual-specific subjective distributions based purely on answers to probabilistic questions, and then link the elicited location and dispersion of the subjective distributions to other observed variables to study the relationship between them. See, for example, Dominitz and Manski (1997b), and Hurd et al. (2011b). This method ignores issues on sample selection, rounding and focal points in respondents' answers, and other survey behaviors. The second strategy is to construct and estimate a structural model that explicitly takes into account the answering process in surveys, and to elicit the subjective distribution and estimate its relationship with other variables simultaneously, see, for example, Hudomiet et al. (2011), and De Bresser and van Soest (2013). However, the second way usually involves complex nonlinear dynamics in the underlying model and requires stronger assumptions on unobserved individual effects. As in this paper we will investigate the relationship between stock market expectations and other variables with different assumptions on the unobserved individual effects, we choose the first strategy to make estimations feasible. Moreover, Kleinjans and van Soest (2013) compared results of their model that incorporates reporting behavior with models without this feature, and found that signs and significance levels are quite similar.

We elicit individuals' subjective distributions using a parametric model. Following Dominitz and Manski (1997b) and Hurd et al. (2011b), we assume that stock (log-)returns are normally distributed. We further assume that expected return and volatility are time- and horizon-specific. Denote s_t the stock market price at time t, then have

$$\ln\left(\frac{s_{t+\tau}}{s_t}\right) = \mu_{t,\tau} + z_{t,\tau}, \tag{3.2.1}$$

where $\mu_{t,\tau}$ is the drift term and $z_{t,\tau}$ is the volatility term. We assume that $z_{t,\tau}$ is normally distributed with mean 0 and variance $\sigma^2_{t,\tau}$.

The probability that the stock market price will increase by ξ or more in τ years is

$$\begin{aligned} P\left(\frac{s_{t+\tau}}{s_t} > \xi\right) &= P\left(\ln\frac{s_{t+\tau}}{s_t} > \ln\xi\right) \\ &= \Phi\left(\frac{\mu_{t,\tau} - \ln\xi}{\sigma_{t,\tau}}\right). \end{aligned} \tag{3.2.2}$$

For each survey time t and each forecast horizon τ, there are two unknown parameters, $\mu_{t,\tau}$ and $\sigma_{t,\tau}$. For a given respondent i, we observe the subjective probability for three values of ξ (1.0, 1.2, and 0.8). We can estimate $\mu_{t,\tau}$ and $\sigma_{t,\tau}$ using nonlinear least squares based on the following equation

$$\sum_j \left(p_{ijt} - \Phi\left(\frac{\mu_{t,\tau} - \ln\xi_j}{\sigma_{t,\tau}}\right)\right)^2, \tag{3.2.3}$$

where $j \in (1,2,3)$, with $\xi_1 = 0.8$, $\xi_2 = 1$, and $\xi_3 = 1.2$.

We fit model (3.2.3) at the individual- and wave- level at both horizons. In the model we allow for inconsistent probabilistic answers.[4] However, sometimes the magnitudes of the estimated μ and σ from inconsistent answers are implausibly large. To have stable estimates, we add a lower and an upper bound to the probabilities of changes in stock prices. To be specific, we assume that stock prices will not decrease by more than 90 % and will not increase by more than 500 % in ten years. This is equivalent to assuming that $P\left(0.1 \leq \frac{s_{t+\tau}}{s_t} \leq 6\right) = 1$.[5]

[4]The fractions of inconsistent probabilistic answers are 15% and 25% for the one-year expectations and the ten-year expectations, respectively.

[5]The bounds are based on historical distributions of the Dow Jones Industrial Average (DJIA) index values. The results in the following analysis are robust to modest variations of the boundaries.

3.3 Descriptive analysis and sample selection

We start with looking at some general patterns of households' stock market expectations. Table 3.1 presents some descriptive statistics of our sample. While questions on one-year expectations are asked monthly, questions on ten-year expectations are asked in the survey roughly every three months. To maintain comparability, we select only waves with all the six questions regarding expectations at the two horizons. Besides, although we allow for inconsistent probabilistic answers when fitting the subjective distributions, we exclude responses that correspond to only one point on the distribution curve. For example, we drop observations with "50%" answers to all the three questions regarding the same forecast horizon. Compared to one-year expectations, people in the survey are more likely to report that, in ten years, the chance of an increase and the chance of a more-than-20% increase are both 100, and that the chance of a more-than-20% decrease is 0. This results in a larger reduction in sample size for the ten-year expectations, as seen in table 3.1. We annualize the subjective ten-year return and ten-year uncertainty to make the figures comparable across forecast horizons. The elicited subjective stock returns (μ) are rather low compared to the stock returns from historical data Previous literature gives similar findings (Hurd & Rohwedder, 2011), and this observation is used to explain the "stock participation puzzle", that is, only a limited amount of people have stocks in reality, while by theory everyone should holds a certain amount of stocks. There is a large variation in most variables, including the expected return and volatility at both horizons. Besides, the ten-year expected return is much higher than the one-year counterpart, even after annualization. The range of the elicited uncertainty (σ) is rather wide. We also have investigated which kine of people tend to report very large subjective uncertainty. The results are shown in the appendix.

Figure 3.1 shows the scatter plots of the elicited subjective μ and σ for different horizons. It seems that the subjective uncertainty is positively related to the absolute value of the subjective return, at both horizons. The correlation coefficients

Table 3.1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
μ (%, one-year)	-0.89	17.5	-119.47	88.51	15470
σ (%, one-year)	27.32	27.26	0.02	168.58	15470
μ (%, ten-year annualized)	1.4	2.59	-11.27	9.1	14497
σ (%, ten-year annualized)	11.5	9.79	0.01	53.31	14497
Female	0.56	0.5	0	1	16019
White	0.91	0.29	0	1	16019
Age	51.12	14.59	17	97	16019
Bachelor	0.46	0.5	0	1	16019
Health	3.47	0.91	1	5	16018
Income per capita ($1000)	50.45	44.26	0.36	250	15977
Follow stock	1.69	0.62	1	3	15553
Understand stock	3.3	1.18	1	6	15553
Eco Sentiment	0.55	0.22	0	1	15970
Non-Eco Sentiment	0.66	0.16	0	1	16014

between the subjective uncertainty and the absolute value of the subjective return is 0.43 and 0.45 for the one-year horizon and the ten-year horizon, respectively. This implies that people who expect very large changes in stock prices also have higher uncertainty.

In the following we examine how stock market expectations at different horizons vary over time. Figure 3.2 plots the mean values of elicited expected stock return (μ) and volatility (σ) at both one-year and ten-year horizons. One-year expected returns are almost always negative while ten-year expected returns are always positive. Besides, the (annualized) ten-year volatility is much smaller than the one-year volatility. Thus, it seems that long-term expectations are constantly more optimistic than one-year expectations. In addition, while the one-year mean fluctuates over time, the long-run mean is more stable, showing a declining trend. Recently, Pástor and Stambaugh (2012) argued that stock returns are more risky over longer horizons. They show that annualized subjective volatility of long-term stock returns is much higher than the volatility of one-year returns, based on a survey for corporate Chief Financial Officers (CFOs).[6] This is not the case for households' expectations

[6]They use a survey that asks CFOs to give the 10th and 90th percentiles of a confidence interval for the annualized excess equity return for both one-year and ten-year horizons. A given

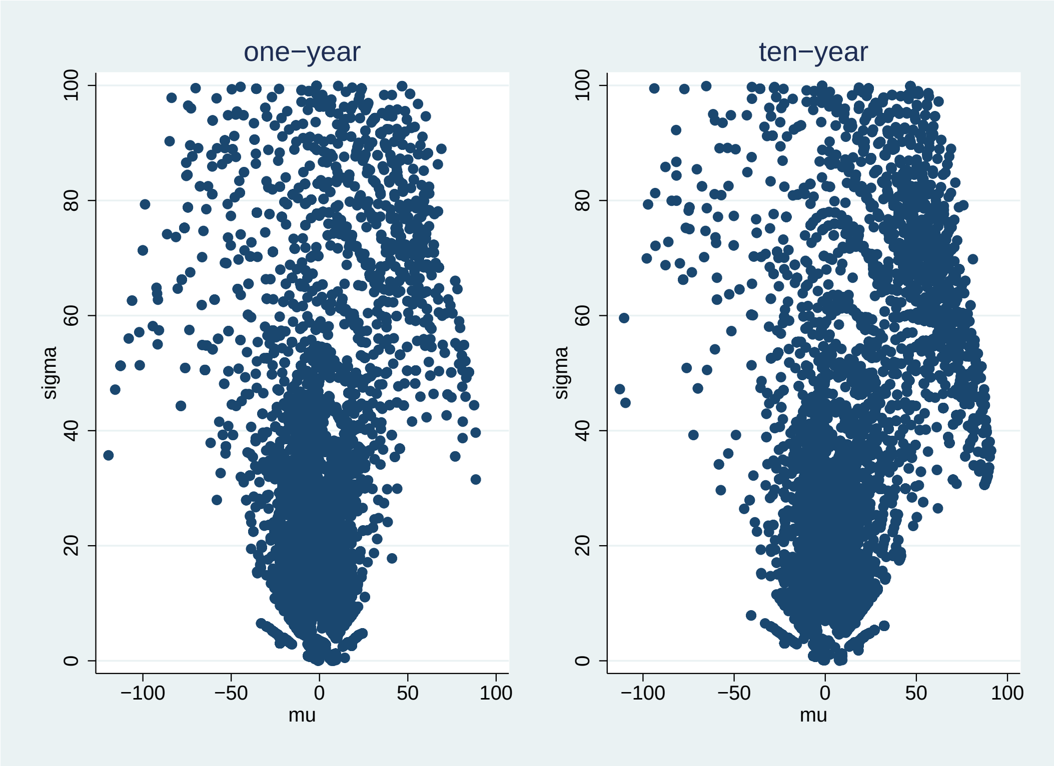


Figure 3.1: Subjective return and uncertainty: scatter plot

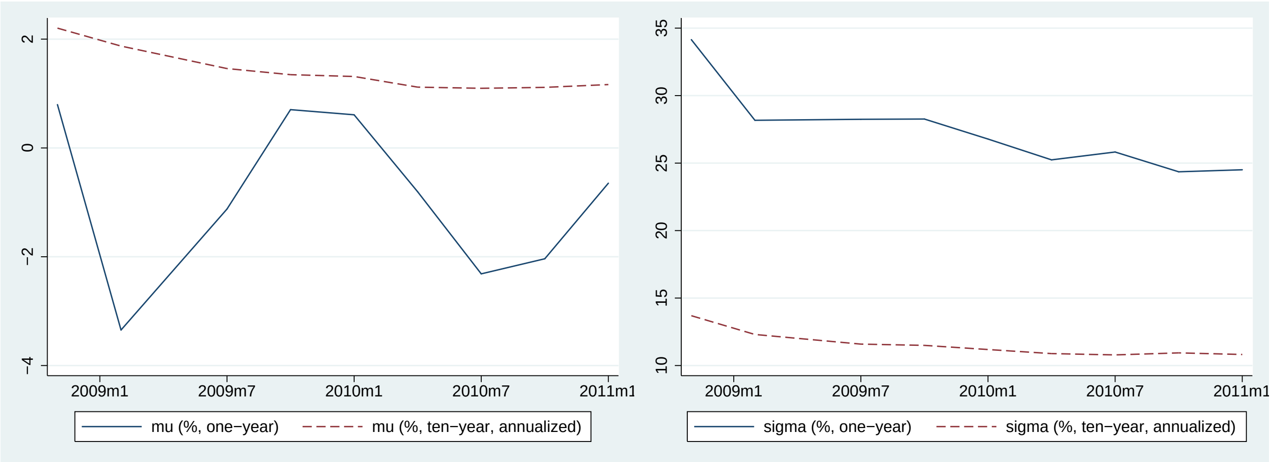
if we simply annualize the ten-year volatility by dividing it by $\sqrt{10}$. Our results also indicate expected return and volatility are horizon-specific, as the estimates at different horizons cannot be matched by simple annualization.

Table 3.2 shows the frequency of μ in each quintile for the one-year horizon and the ten-year horizon. Table 3.3 shows the frequency distribution for σ. These tables indicate that expectations at different horizons are highly correlated with each other.

respondent's subjective probability distribution is elicited based on the normal distribution.

Table 3.2: Frequency distribution of μ in each quintile

	μ (ten-year)					
μ (one-year)	1	2	3	4	5	Total
1	57.7	16.8	10.1	8.4	6.4	20.4
2	20.2	36.6	21.7	14.4	11.4	21.5
3	10.3	22.7	30.3	24.2	18.8	21.4
4	6.0	15.3	23.2	29.6	25.5	19.6
5	5.7	8.6	14.8	23.3	37.9	17.2
Total	100.0	100.0	100.0	100.0	100.0	100.0



(a) μ (b) σ

Figure 3.2: Time patterns of stock market expectations

Table 3.3: Frequency distribution of σ in each quintile

	σ (ten-year)					
σ (one-year)	1	2	3	4	5	Total
1	61.9	23.3	12.4	7.2	4.5	22.1
2	13.5	42.1	24.7	16.5	10.9	21.8
3	11.6	21.9	30.5	23.2	18.7	21.3
4	7.0	9.7	22.9	31.5	26.3	19.3
5	5.9	3.1	9.5	21.6	39.6	15.5
Total	100.0	100.0	100.0	100.0	100.0	100.0

Table 3.4: Transition matrices: elicited μ (one year)

μ quantile	1	2	3	4	5	Total
1	57.7	16.8	10.1	8.4	6.4	20.4
2	20.2	36.6	21.7	14.4	11.4	21.5
3	10.3	22.7	30.3	24.2	18.8	21.4
4	6.0	15.3	23.2	29.6	25.5	19.6
5	5.7	8.6	14.8	23.3	37.9	17.2
Total	100.0	100.0	100.0	100.0	100.0	100.0

We are also interested in how persistent individuals' views on stock market returns are. The degree of persistence in expectations can be examined descriptively by transition matrices. Tables 3.4 and 3.5 present the transition matrices for the subjective mean and the volatility at the one-year horizon, respectively. Tables 3.6 and 3.7 show corresponding transition matrices for the ten-year expectations. The rows indicate expectations at time $t-1$ while the columns indicate expectations at time t.

If there is no persistence in subjective expectations, we are likely to observe that entries in the transition matrix are all approximately one-fifth. In contrast, numbers on the diagonal are much larger than 0.2. Furthermore, the further from the diagonal, the smaller the numbers are. The results indicate a high level of persistence in both the expected mean and volatility at different horizons. For those categorized into the first quintile (the most pessimistic) of the distribution of expected one-year returns (μ) in a give wave, there is a 58% chance that they stay at the first quintile in the following period (after three months). The chance of remaining to be the most optimistic in the following period is 38%. It could also be expected that long-term expectations will be more persistent than short-term expectations, as the former might be less affected by short-term fluctuations. For example, Dräger and Lamla (2012) found that households' long-term inflation expectations are updated less frequently than short-run expectations. The transition matrices in general support this argument, although the differences are modest.

Table 3.5: Transition matrices: elicited σ (one year)

σ quantile	1	2	3	4	5	Total
1	52.4	18.4	11.4	8.7	8.2	20.2
2	20.7	32.5	22.6	15.6	11.1	20.9
3	12.0	23.7	29.7	24.5	16.8	21.5
4	8.8	16.3	22.2	28.8	24.2	19.9
5	6.1	9.1	14.2	22.4	39.6	17.6
Total	100.0	100.0	100.0	100.0	100.0	100.0

Table 3.6: Transition matrices: elicited μ (ten year)

μ quantile	1	2	3	4	5	Total
1	61.0	24.9	9.0	3.2	2.5	20.7
2	25.0	41.0	20.5	8.9	6.2	20.7
3	7.1	20.5	34.8	24.5	13.8	20.3
4	4.6	8.6	21.7	40.5	25.3	19.8
5	2.3	5.0	14.0	22.8	52.1	18.5
Total	100.0	100.0	100.0	100.0	100.0	100.0

Table 3.7: Transition matrices: elicited σ (ten year)

σ quantile	1	2	3	4	5	Total
1	57.7	16.8	10.1	8.4	6.4	20.4
2	20.2	36.6	21.7	14.4	11.4	21.5
3	10.3	22.7	30.3	24.2	18.8	21.4
4	6.0	15.3	23.2	29.6	25.5	19.6
5	5.7	8.6	14.8	23.3	37.9	17.2
Total	100.0	100.0	100.0	100.0	100.0	100.0

3.4 Sources of persistence: static panel data model

One explanation for the persistence in stock market expectations is that expectations are related to observed or unobserved time-invariant individual characteristics. To examine this issue, in this section we estimate a static panel data model, which has the following general form:

$$y_{it} = X_{it}'\beta + Z_i'\lambda + u_i + \epsilon_{it}, \tag{3.4.1}$$

where y_{it} is some characteristic of the subjective distribution (μ or σ in our case) of individual i at time t, X_{it} is a column vector of time varying covariates, Z_i is a column vector of time invariant regressors, u_i is the unobserved individual effect, ϵ_{it} is an idiosyncratic term, and β and λ are unknown parameter vectors. In the next section we will also consider dynamic panel data models.[7]

We estimate model (3.4.1) using both the random effects specifications (RE) and the fixed effects specifications (FE). The RE specification assumes that there is no correlation between observed regressors and the unobserved individual effect while the FE specification allows for arbitrary correlation between the unobserved individual effect and the observed covariates. In both cases ϵ_{it} is an idiosyncratic error term, with mean zero and constant variance. A Hausman test will be used to test which specification is more appropriate.

Table 3.8 reports the estimation results for the elicited μ at both the short- and long-run horizons. The results of the Hausman tests suggest that the random effects estimates are not consistent. Males, wealthy people, higher educated people and people, who follow and understand the stock market, on average have a higher μ at both horizons. These findings regarding the demographic variables are largely consistent with those in previous studies. Our contribution is that we show that this pattern of heterogeneity exists for expectations at both the short and the long hori-

[7] In the appendix we estimate a similar model, replacing time dummies with past stock returns.

zons. It can also be seen that the gap in terms of stock market expectations between different socio-demographic groups is larger for long-term expectations. In addition, measures of sentiment, especially economic sentiment, are positively related to stock market expectations under different specifications. This can be related to the recent finding in Kaplanski et al. (2013b) that happy people tend to have more optimistic stock return expectations. Our results do not only provide additional empirical evidence in this direction, but also highlight the relative importance of economic sentiment vs. the noneconomic sentiment. Moreover, the coefficients of the socio-economic variables are in general of a larger magnitude for the ten-year expectations. This indicate that the gap in expectations across socio-economic groups are larger in the long-term. As long-term stock market expectations might be more important for the stock holding decisions, the result is consistent with the fact that lower educated people rarely participate in the stock market.

Table 3.9 presents the panel data estimation results for the elicited volatility. We use $\log \sigma$ instead of σ as the dependent variable to mitigate the impacts of outliers and truncation. The finding that older people expect lower volatility of future stock returns is also documented in Hurd et al. (2011b) and in Hudomiet et al. (2011). However, we also find that more educated people and people who follow the stock market have high volatility about stock returns, which is in the opposite direction to the findings in Hudomiet et al. (2011) who use data from the Health and Retirement Study. As there is little theory to guide us at this point, we conclude that the subjective volatility is not always consistently explained and more empirical evidence is required. In addition, we also find that economic sentiment is negatively related to volatility. While Kaplanski et al. (2013b) find that non-economic sentiment can negatively affect risk expectations, we find that only the effects of economic sentiment are significant.

Table 3.8: Static panel data model estimates:μ (%)

	One-year		Ten-year	
	RE	FE	RE	FE
Female	-1.446**		-4.964**	
	(0.507)		(0.766)	
White	-0.034		2.945*	
	(0.816)		(1.226)	
Age	0.027	0.825*	0.028	0.454
	(0.017)	(0.328)	(0.026)	(0.438)
Bachelor	3.758**	3.868+	9.987**	3.933
	(0.508)	(2.323)	(0.761)	(3.117)
Health	0.378+	0.263	-0.304	-1.076**
	(0.224)	(0.296)	(0.319)	(0.404)
Income per capita ($1000)	0.023**	0.020*	0.028**	-0.011
	(0.005)	(0.009)	(0.008)	(0.012)
Follow stock	0.425	-0.981*	2.937**	0.329
	(0.360)	(0.446)	(0.508)	(0.609)
Understand stock	0.807**	0.433+	1.656**	0.232
	(0.196)	(0.263)	(0.277)	(0.355)
Eco Sentiment	3.766**	2.646*	4.341**	4.832**
	(0.913)	(1.110)	(1.288)	(1.521)
Non-Eco Sentiment	3.037*	2.651+	3.651*	3.770*
	(1.203)	(1.380)	(1.679)	(1.885)
Num.Obs	14930	14930	13985	13985
Num.Ind	2508	2508	2483	2483
σ_u	10.304	17.115	15.909	20.922
σ_e	13.576	13.576	17.717	17.717
ρ	0.366	0.614	0.446	0.582
Hausman p-value	0.000		0.000	

A constant term and time dummies are included but the coefficients are not reported to save space. ρ is the fraction of variance due to unobserved individual effect. "Num.Obs " refers to the number of total observations. "Num.Ind " refers to the number of individuals. Statistical significance is indicated as follows: + $p<0.10$, * $p<0.05$, ** $p<0.01$.

Table 3.9: Static panel data model estimates:$\log \sigma$ (%)

	One-year		Ten-year	
	RE	FE	RE	FE
Female	1.007		4.871	
	(3.454)		(3.787)	
White	10.232+		13.429*	
	(5.552)		(6.063)	
Age	-0.532**	0.161	-0.302*	2.019
	(0.118)	(2.081)	(0.129)	(2.150)
Bachelor	15.460**	4.041	14.219**	3.831
	(3.439)	(14.753)	(3.758)	(15.288)
Health	3.482*	5.140**	2.825+	4.199*
	(1.460)	(1.882)	(1.560)	(1.982)
Income per capita ($1000)	0.006	-0.028	-0.015	-0.033
	(0.035)	(0.058)	(0.038)	(0.061)
Follow stock	7.729**	3.157	10.158**	5.774+
	(2.330)	(2.832)	(2.484)	(2.988)
Understand stock	5.491**	2.101	3.901**	0.436
	(1.278)	(1.672)	(1.354)	(1.739)
Eco Sentiment	-20.442**	-21.716**	-23.861**	-22.308**
	(5.901)	(7.051)	(6.299)	(7.458)
Non-Eco Sentiment	-6.039	-0.982	-1.181	9.250
	(7.730)	(8.762)	(8.197)	(9.242)
Num.Obs	14930	14930	13985	13985
Num.Ind	2508	2508	2483	2483
σ_u	72.218	86.157	79.645	98.524
σ_e	86.215	86.215	86.890	86.890
ρ	0.412	0.500	0.457	0.562
Hausman p-value	0.000		0.004	

A constant term and time dummies are included but the coefficients are not reported to save space. ρ is the fraction of variance due to unobserved individual effect. "Num.Obs " refers to the number of total observations. "Num.Ind " refers to the number of individuals. Statistical significance is indicated as follows: + $p<0.10$, * $p<0.05$, ** $p<0.01$.

3.5 Sources of persistence: dynamic panel data models

Apart from unobserved time-invariant effects, persistence in expectations can also result from state-dependence, which is the impact of current expectation on expectations in future periods. This might be relevant if households form expectations based on some Bayesian learning strategies so that they update their forecasts by combining old forecast with new information, or, if some shocks to expectations can last for more than one period, because households learn information in these shocks gradually. In this section we further exploit the dynamics in stock market expectations based on dynamic panel data models.

3.5.1 Models

To better understand the sources of persistence in stock market expectations and the relationship between expectations and other observed factors, we specify a dynamic panel data model, which has the following general form:

$$y_{it} = \gamma y_{i,t-1} + X_{it}'\beta + Z_i'\lambda + u_i + \epsilon_{it}. \tag{3.5.1}$$

The model is similar to model (3.4.1). The difference here is that we add the lagged dependence variable as a regressor to capture the level of state dependence, with a regression coefficient γ satisfying $|\gamma| < 1$. To check the robustness of the result, we compare different estimators for the general model (3.5.1). These estimators will be consistent under different assumptions, which are summarized in the following:

- Ordinary Least Squares estimation. The OLS estimation will be consistent in the absence of an unobserved individual effect u_i. Otherwise, the estimation of γ by OLS will be biased upwards, as the estimated γ will reflect both state dependence and unobserved heterogeneity (Hauck and Rice (2004)).

- Fixed Effects with lagged dependent variable (FE). The FE estimation will be consistent if γ is zero (no state-dependence). In the presence of state-dependence, FE estimation is still consistent when T is allowed to go to infinity. For short panels with state dependence, FE estimation of γ will be biased downwards (Nickell (1981)).

- Conditional maximum likelihood estimation (CMLE). The CMLE uses a likelihood function based on the joint distribution of the observations conditional on initial observations ($y_{i,0}$). We parameterize the distribution of the unobserved individual effects as

$$u_i = \theta_1 + \theta_2 y_{i,0} + \bar{X}_i' \theta_3 + \xi_i, \tag{3.5.2}$$

  where $\bar{X}_i$ is a column vector of the within-individual mean values of the time-varying covariates over the sample period. This method is consistent if the distribution of the unobserved individual effects is correctly specified.

- Arellano and Bond's GMM method (GMM). This method utilizes levels of the lagged dependent variable to construct instruments for the first-differenced lagged dependent variables. The GMM estimator is consistent if the moment conditions are valid, which can be checked based on overidentification tests and tests of serial autocorrelation in the residuals.

Table 3.10 shows coefficient estimates and other relevant statistics for the one-year expectations based on the four specifications, respectively. Table 3.11 presents the results for the ten-year expectations. The OLS estimates for the lagged dependent variable are largest for expectations at both horizons, likely due to the existence of an unobserved individual effect. The coefficient for one-year μ is 0.4 while for ten-year μ is 0.5. Once the unobserved heterogeneity is controlled for, as in the other three specifications, the coefficients in front of the lagged dependent variable become substantially lower. The fixed effect estimates of this coefficient are the smallest and are slightly negative. This is consistent with the fact that FE estimation of state-dependence is biased downwards (Nickell (1981)). The GMM estimates are only significant at the 10% level for the one-year expectations and not significantly different from zero for the ten-year expectations. The instruments in the GMM estimations seem to be appropriate as the models pass the Sargan test of over-identifying restrictions and the test for second-order serial correlation in the residuals. The levels of state-dependence based on the CMLE specification are around 0.15 for both horizons. The proportion of variance due to time-invariant unobservable factors is 0.28 for the one-year expectations and 0.35 for the ten-year expectations under CMLE. Above all, the estimation results from the different specifications suggest that the level of state-dependence in the stock market expectations is most likely around 0.2 (based on the GMM estimation) and the unobserved time-invariant individual effects seem to be more important to explain the persistence in expectations.

Tables 3.12 and 3.13 present the dynamic panel data estimation results for the log-volatility, represented by $\log(\sigma)$, for the expectations at different horizons. The levels of state-dependence in the volatility are similar to the ones in the expected returns. The OLS and FE estimates provide upper and lower bounds, respectively. Again, unobserved individual effects are more important.

3.6 Revisions of expectations

In the previous sections we focused on the levels of stock market expectations. As we have documented, levels of expectations at different horizons are strongly related to time-invariant individual effects. In addition, the previous literature on heterogeneity in stock market expectations across people focuses on the heterogeneity in the levels of the expectations. As our results suggest, this heterogeneity is likely to

Table 3.10: Dynamic panel data model estimates:μ (one year)

	OLS	CMLE	FE	GMM
μ_{t-1}	0.405**	0.149**	-0.019*	0.229+
	(0.008)	(0.010)	(0.009)	(0.119)
μ_0		0.137**		
		(0.011)		
Female	-0.780**	-1.061*		
	(0.285)	(0.454)		
White	0.138	-0.103		
	(0.478)	(0.735)		
Age	-0.004	0.588+	0.637+	0.281
	(0.010)	(0.314)	(0.330)	(0.407)
Bachelor	2.200**	1.457	-0.807	-3.540
	(0.291)	(2.875)	(3.023)	(5.075)
Health	0.330+	0.037	-0.028	0.069
	(0.180)	(0.329)	(0.331)	(0.451)
Income per capita ($1000)	0.010**	0.017	0.022*	0.022
	(0.003)	(0.011)	(0.011)	(0.018)
Follow stock	0.803**	-0.889+	-0.804	-0.190
	(0.295)	(0.498)	(0.500)	(0.901)
Understand stock	0.411**	-0.061	0.023	0.285
	(0.155)	(0.298)	(0.301)	(0.530)
Eco Sentiment	2.600**	3.507**	3.082*	5.845**
	(0.781)	(1.221)	(1.225)	(1.772)
Non-Eco Sentiment	2.371*	1.460	2.277	-0.120
	(1.078)	(1.513)	(1.516)	(2.078)
Num.Obs	11198	11198	11198	8494
Num.Ind		2184	2184	1852
σ_u		0.077	0.158	
σ_e		0.122	0.120	
ρ		0.284	0.634	
AR(2)				0.132
Sargan				0.309

A constant term and time dummies are included but the coefficients are not reported to save space. ρ is the fraction of variance due to unobserved individual effect. The GMM estimation uses all available lags of the dependent variable in levels dated $t-1$ or earlier as instruments. "Sargan" reports the p-value of the Sargan test of over-identifying restrictions. "AR(2) " reports the p-value of the test of autocorrelation in residuals of order 2. We found that the residuals from the CMLE estimation are autocorrelated. "Num.Obs " refers to the number of total observations. "Num.Ind" refers to the number of individuals. Statistical significance is indicated as follows: + $p<0.10$, * $p<0.05$, ** $p<0.01$.

Table 3.11: Dynamic panel data model estimates:μ (ten year)

	OLS	CMLE	FE	GMM
μ_{t-1}	0.495**	0.161**	-0.044**	-0.176
	(0.008)	(0.012)	(0.010)	(0.170)
μ_0		0.189**		
		(0.014)		
Female	-2.044**	-2.564**		
	(0.424)	(0.712)		
White	1.090	1.626		
	(0.700)	(1.141)		
Age	-0.023	-0.095	0.046	-0.284
	(0.015)	(0.473)	(0.468)	(0.492)
Bachelor	4.610**	-0.867	1.290	1.904
	(0.437)	(4.106)	(4.212)	(6.430)
Health	0.123	-0.227	-0.397	-0.405
	(0.266)	(0.481)	(0.482)	(0.548)
Income per capita ($1000)	0.020**	0.014	0.018	0.017
	(0.005)	(0.016)	(0.016)	(0.021)
Follow stock	2.765**	0.982	1.231+	1.763+
	(0.442)	(0.729)	(0.731)	(1.065)
Understand stock	0.804**	-0.137	-0.070	-0.015
	(0.229)	(0.424)	(0.427)	(0.621)
Eco Sentiment	1.428	3.214+	2.453	4.811*
	(1.156)	(1.790)	(1.793)	(2.110)
Non-Eco Sentiment	2.593	1.969	2.048	-0.364
	(1.591)	(2.242)	(2.243)	(2.518)
Num.Obs	10147	10147	10147	7538
Num.Ind		2100	2100	1750
σ_u		0.122	0.213	
σ_e		0.168	0.164	
ρ		0.346	0.627	
AR(2)				0.299
Sargan				0.100

A constant term and time dummies are included but the coefficients are not reported to save space. ρ is the fraction of variance due to unobserved individual effect. The GMM estimation uses all available lags of the dependent variable in levels dated $t-1$ or earlier as instruments. "Sargan" reports the p-value of the Sargan test of over-identifying restrictions. "AR(2) " reports the p-value of the test of autocorrelation in residuals of order 2. We found that the residuals from the CMLE estimation are autocorrelated. "Num.Obs " refers to the number of total observations. "Num.Ind" refers to the number of individuals. Statistical significance is indicated as follows: + p<0.10, * p<0.05, ** p<0.01.

Table 3.12: Dynamic panel data model estimates:log(σ) (one year)

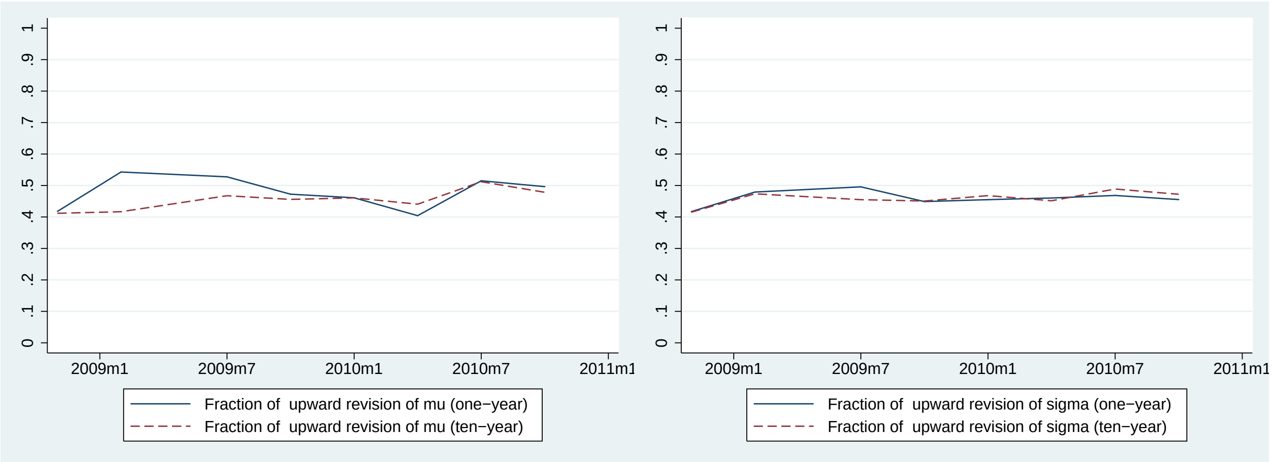
	OLS	CMLE	FE	GMM
$\log(\sigma_{t-1})$	0.418**	0.138**	-0.051**	0.224
	(0.008)	(0.011)	(0.010)	(0.229)
$\log(\sigma_0)$		0.152**		
		(0.013)		
Female	0.190	0.797		
	(1.903)	(3.120)		
White	4.829	7.639		
	(3.198)	(5.045)		
Age	-0.349**	0.828	-1.344	-0.886
	(0.067)	(2.092)	(2.183)	(2.744)
Bachelor	8.844**	-20.927	-19.607	-29.233
	(1.945)	(19.126)	(19.979)	(34.621)
Health	2.048+	5.422*	4.806*	6.461*
	(1.202)	(2.186)	(2.186)	(3.167)
Income per capita ($1000)	-0.007	0.029	-0.006	0.071
	(0.022)	(0.072)	(0.072)	(0.119)
Follow stock	5.387**	1.429	2.684	7.431
	(1.973)	(3.307)	(3.305)	(6.143)
Understand stock	3.551**	0.409	0.721	1.856
	(1.036)	(1.978)	(1.992)	(3.564)
Eco Sentiment	-15.856**	-20.671*	-19.456*	-17.300
	(5.223)	(8.111)	(8.104)	(12.150)
Non-Eco Sentiment	2.167	3.092	5.042	-7.880
	(7.204)	(10.049)	(10.025)	(13.791)
Num.Obs	11198	11198	11198	8494
Num.Ind		2184	2184	1852
σ_u		0.539	0.928	
σ_e		0.813	0.793	
ρ		0.306	0.578	
AR(2)				0.470
Sargan				0.197

A constant term and time dummies are included but the coefficients are not reported to save space. ρ is the fraction of variance due to unobserved individual effect. . "Sargan" reports the p-value of the Sargan test of over-identifying restrictions. "AR(2) " reports the p-value of the test of autocorrelation in residuals of order 2. We found that the residuals from the CMLE estimation are autocorrelated. "Num.Obs " refers to the number of total observations. "Num.Ind" refers to the number of individuals. Statistical significance is indicated as follows: + $p<0.10$, * $p<0.05$, ** $p<0.01$.

Table 3.13: Dynamic panel data model estimates:log(σ) (ten year)

	OLS	CMLE	FE	GMM
log(σ_{t-1})	0.468**	0.185**	-0.031**	-0.157
	(0.009)	(0.012)	(0.011)	(0.179)
log(σ_0)		0.171**		
		(0.015)		
Female	2.490	5.030		
	(2.042)	(3.275)		
White	5.472	10.374*		
	(3.378)	(5.261)		
Age	-0.277**	1.352	1.983	2.886
	(0.072)	(2.333)	(2.297)	(2.407)
Bachelor	11.587**	-19.454	-8.307	-12.767
	(2.087)	(20.183)	(20.697)	(32.810)
Health	1.962	5.281*	4.908*	1.469
	(1.286)	(2.371)	(2.368)	(2.717)
Income per capita ($1000)	0.003	-0.017	-0.022	-0.089
	(0.024)	(0.077)	(0.077)	(0.105)
Follow stock	6.908**	1.823	2.147	6.078
	(2.125)	(3.589)	(3.594)	(5.517)
Understand stock	3.028**	1.859	1.759	4.892
	(1.104)	(2.090)	(2.099)	(3.107)
Eco Sentiment	-6.317	-16.773+	-19.884*	-4.942
	(5.582)	(8.824)	(8.808)	(10.329)
Non-Eco Sentiment	-0.971	0.280	0.587	-18.321
	(7.675)	(11.052)	(11.023)	(12.808)
Num.Obs	10147	10147	10147	7538
Num.Ind		2100	2100	1750
σ_u		0.546	1.008	
σ_e		0.832	0.807	
ρ		0.301	0.610	
AR(2)				0.344
Sargan				0.001

A constant term and time dummies are included but the coefficients are not reported to save space. ρ is the fraction of variance due to unobserved individual effect. The GMM estimation uses all available lags of the dependent variable in levels dated $t-1$ or earlier as instruments. "Sargan" reports the p-value of the Sargan test of over-identifying restrictions. "AR(2) " reports the p-value of the test of autocorrelation in residuals of order 2. We found that the residuals from the CMLE estimation are autocorrelated. "Num.Obs " refers to the number of total observations. "Num.Ind" refers to the number of individuals. Statistical significance is indicated as follows: + p<0.10, * p<0.05, ** p<0.01.



(a) Revision of μ (b) Revision of σ

Figure 3.3: Time patterns of updates in stock market expectations

reflect differences in terms of time-invariant factors, which says little about differences in the formation of expectations. In this section we examine the dynamics of updates or revisions in expectations, which are the differences between expectations in two subsequent periods. This is more related to how individuals react to news or shocks.

3.6.1 How changes in expectations vary across people and horizons

Figure 3.3 plots the fractions of people that update expectations upwards at each period. The fractions fluctuate around 0.5 during our two-year sample period.

Furthermore, heterogeneity in expectation revisions does not only occur between respondents, but also exists across horizons within individuals. Table 3.14 shows contemporarily the frequency of $\Delta\mu$ in each quintile at one-year and ten-year expectations. Unlike the case for levels, changes in expected return at different horizons are not that closely related. For example, there is more than 15% chance that updates in one-year and ten-year expected returns lie in two extreme quintiles. Similar patters are found for the updates in the expected volatility, which are shown in Ta-

Table 3.14: Frequency distribution of changes in μ in each quintile

	$\Delta\mu$ (ten-year)					
$\Delta\mu$ (one-year)	1	2	3	4	5	Total
1	33.6	20.0	11.9	13.0	16.2	18.9
2	20.5	26.4	21.9	19.2	14.8	20.6
3	14.9	20.6	33.4	20.3	14.3	20.8
4	15.2	19.3	20.0	27.4	20.0	20.4
5	15.8	13.6	12.9	20.1	34.7	19.4
Total	100.0	100.0	100.0	100.0	100.0	100.0

Table 3.15: Frequency distribution of changes in σ in each quintile

	$\Delta\sigma$ (ten-year)					
$\Delta\sigma$ (one-year)	1	2	3	4	5	Total
1	37.1	20.1	12.2	13.7	13.3	19.2
2	20.8	29.7	20.3	17.6	14.8	20.7
3	13.7	19.8	38.5	19.8	12.0	20.9
4	15.2	17.4	19.2	28.4	22.3	20.5
5	13.1	13.0	9.9	20.6	37.6	18.7
Total	100.0	100.0	100.0	100.0	100.0	100.0

ble 3.15. The results indicate that individuals update expectations quite differently across horizons.

3.6.2 A vector autoregressive model for expectation revisions

To investigate how shocks to expectations last over time, we estimate the following vector autoregressive model:

$$\Delta Y_{it} = \alpha + \sum_{\tau=1}^{\tau} B_\tau \Delta Y_{i,t-p} + CX_{it} + \epsilon_{it}, \tag{3.6.1}$$

where α is a vector of constant terms, ΔY is a column vector including expectations at one-year and ten-year horizons, X refers to a vector of control variables that are assumed to be exogenous, and ϵ_{it} is an error term with mean zero and constant variance. B_τ and C are matrices of unknown parameters.

Table 3.16 presents the results of model (3.6.1).[8] We observe negative autocor-

[8]Demographic variables and time dummies are included as exogenous variables. However, coefficients of demographic variables are not significant. The coefficients of the demographic variables

Table 3.16: Panel vector autoregression

	$\Delta\mu$ (1y)	$\Delta\mu$ (10y)
$\Delta\mu_{-1}$ (1y)	-0.532**	-0.015
	(0.012)	(0.019)
$\Delta\mu_{-2}$ (1y)	-0.215**	-0.003
	(0.011)	(0.017)
$\Delta\mu_{-1}$ (10y)	0.020*	-0.555**
	(0.008)	(0.013)
$\Delta\mu_{-2}$ (10y)	0.007	-0.258**
	(0.008)	(0.012)
Num.Obs	5489	5395

$\Delta\mu_{-\tau}$ refers to the $\Delta\mu$ lagged τ period. "Num.Obs " refers to the number of total observations. Statistical significance is indicated as follows: + p<0.10, * p<0.05, ** p<0.01.

relation with a magnitude smaller than one for expectations at each horizons. In addition, shocks to long-run expectation updates positively Granger-cause short-run expectation updates. This implies that a positive shock to long-term expectations will also increase short-term expectations in the next period, but not the reverse.

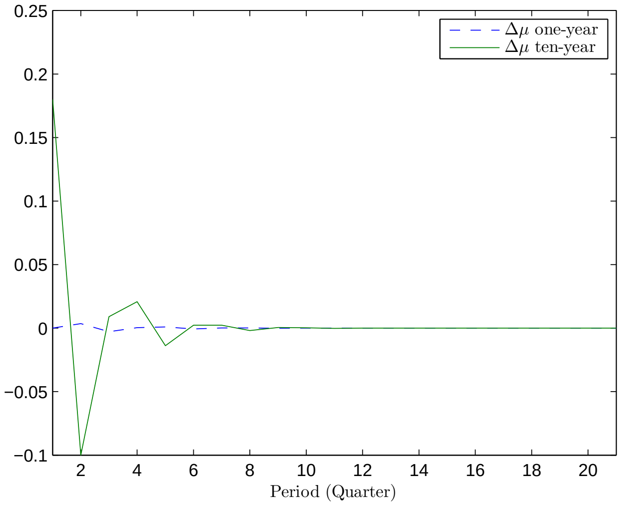
To further investigate the dynamics of changes in expectations, figure 3.4 plots the impulse response of the one-year μ and the ten-year μ, both in first differences and in levels, to a 0.18 shock in the ten-year $\Delta\mu$ respectively.[9] The graph indicates that for first difference, the effect of the shock on the expected ten-year return tends to die off after one year, while the effect on the expected one-year return is only marginal. For levels, there is a permanent increase in the ten-year μ.

3.7 Conclusion

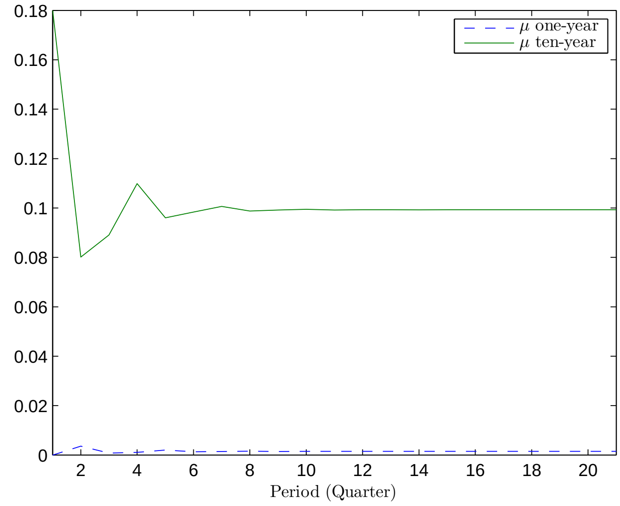
In this paper we have studied the dynamics of households' expected stock return and volatility across time and horizons. On the one hand, expectations are found to be horizon specific and long-term expectations do not match short-term expectations after simple annualization. It seems that households apply different strategies to form stock market expectations at different horizons. On the other hand, ex-

are shown in the appendix.

[9] 0.18 is approximately one standard deviation of $\Delta\mu$ in the sample.



(a) First Difference



(b) Level

Figure 3.4: Impulse response of one-year μ and ten-year μ to a 0.18 shock in ten-year $\Delta\mu$

pectations at different horizons share several common features. First, stock market expectations distribute unevenly across different socio-economic and demographic groups. Males, wealthier people, people with higher education levels, and people who follow the stock market on average report much more optimistic expectations. While this socio-economic and demographic heterogeneity in stock market expectations has been documented before, we show that this pattern is quite profound. The heterogeneity exists for both expected returns and volatility at different horizons, and is quite persistent over time. When further investigating the sources of persistence, we find that the time-invariant unobserved individual effects are quite important compared to the state-dependence in expectations. A further question is why certain groups of people always have more optimistic expectations, when a large part of information in stock market should be publicly available. This might be due to social interactions, difference in financial literacy, or different interpretations of common information. Our study of the revisions of expectations also indicates that households might use different information or interpret information differently when updating expectations.

The findings in this paper suggest several avenues for future research. First, since we show that stock market expectations are horizon specific, it is of interest to examine the mechanism behind this pattern. One possibility is that long-term expectations are mean-reverting, so expected returns at different horizons can have opposite signs. Second, what is exactly the unobserved time-invariant effect that explains a large amount of the variation in the stock market expectations? Is it related to some personal trait of general optimism/pessimism, or exposure to different levels of financial education, or some peer effects? What kind of information is actually used and how does the information shape the beliefs? With current data we are not able to provide definitive answers to these questions. Future research can ask more specific and detailed questions in surveys to better elicit the information content of stock market expectations.

Appendix

3.8 Questions on subjective stock market expectations

The questions about one-year expected change in stock prices reads:

> By next year at this time, what is the percent chance that mutual fund shares invested in blue chip stocks like those in the Dow Jones industrial average will be worth more than they are today?
>
> By next year at this time, what are the chances that mutual fund shares invested in blue-chip stocks like those in the Dow Jones Industrial Average will have increased in value by more than 20 percent compared to what they are worth today?
>
> By next year at this time, what are the chances that mutual fund shares invested in blue-chip stocks like those in the Dow Jones Industrial Average will have fallen in value by more than 20 percent compared to what they are worth today?

The questions about ten-year expected change in stock prices reads:

> What are the chances that mutual fund shares invested in blue chip stocks like those in the Dow Jones Industrial Average will be worth more in 10 years than they are today?
>
> What are the chances that mutual fund shares invested in blue-chip stocks like those in the Dow Jones Industrial Average will have increased in value by more than 20 percent in 10 years compared to what they are worth today?

What are the chances that mutual fund shares invested in blue-chip stocks like those in the Dow Jones Industrial Average will have fallen in value by more than 20 percent in 10 years compared to what they are worth today?

3.9 Additional empirical results

3.9.1 People with very large uncertainty

Table 3.17: Determinants of very large σ: Probit Panel data Model

	One-year	Ten-year
Female	0.136*	0.233**
	(0.064)	(0.060)
White	-0.330**	-0.090
	(0.092)	(0.088)
Age	-0.011**	-0.009**
	(0.002)	(0.002)
Bachelor	-0.138*	-0.173**
	(0.065)	(0.060)
Health	-0.010	-0.028
	(0.034)	(0.032)
Income per capita ($1000)	-0.001	-0.001+
	(0.001)	(0.001)
Follow stock	0.047	0.025
	(0.057)	(0.055)
Understand stock	-0.002	-0.005
	(0.029)	(0.028)
Eco Sentiment	-0.139	-0.282*
	(0.143)	(0.136)
Non-Eco Sentiment	-0.028	-0.139
	(0.198)	(0.186)
Num.Obs	14930	13985
Num.Ind	2508	2483
σ_u	0.837	0.717
ρ	0.412	0.339

A constant term and time dummies are included but the coefficients are not reported to save space. ρ is the fraction of variance due to unobserved individual effect. "Num.Obs " refers to the number of total observations. "Num.Ind " refers to the number of individuals. Statistical significance is indicated as follows: + p<0.10, * p<0.05, ** p<0.01.

It is interesting to examine what kind of people tend to report very large level of uncertainty (σ). We create a dummy variable, which is one if the elicited uncertainty ranks in the top 90th percentile and zero otherwise, for the one-year and ten-year expectations respectively. We regress this indicator on a number of demographic and socio-economic variables, using probit random effects model. Table 3.17shows the estimation results. In general, female, the younger, and the lower educated people tend to have very large uncertainty regarding future stock prices, for both forecast horizons.

3.9.2 Impact of past stock returns

Previous literature indicates that stock market expectations are affected by past stock returns. We do not investigate this issue as the focus of the paper is not on the impact of macroeconomic variables on stock market expectations. Besides, we include a full set of time dummies in the regressions, so including past stock returns would cause multi-collinearity. In this section we replace time dummies in the static panel models with past stock returns, based on the Dow Jones Industrial Average. Table 3.18 reports the estimation results. Past stock returns are not significantly related to the subjective one-year returns, and are negatively related to the subjective ten-year returns. However, as we only have nine periods and the stock return of a given month is the same for every individual,the results are only suggestive.

3.9.3 VAR model

Table 3.19 shows the estimated coefficients of the demographic variables in model (3.6.1).

Table 3.18: Static panel data model estimates:μ (%)

	One-year		Ten-year	
	RE	FE	RE	FE
Past stock return	-0.000	0.001	-0.038**	-0.029**
	(0.001)	(0.002)	(0.002)	(0.003)
Female	-1.428**		-4.853**	
	(0.508)		(0.768)	
White	-0.018		2.926*	
	(0.817)		(1.230)	
Age	0.023	-0.273	0.013	-1.508**
	(0.017)	(0.222)	(0.026)	(0.297)
Bachelor	3.759**	3.586	9.861**	3.279
	(0.508)	(2.335)	(0.763)	(3.132)
Health	0.349	0.245	-0.194	-0.992*
	(0.225)	(0.298)	(0.320)	(0.406)
Income per capita ($1000)	0.021**	0.014	0.025**	-0.018
	(0.005)	(0.009)	(0.008)	(0.013)
Follow stock	0.526	-0.859+	3.448**	0.772
	(0.357)	(0.443)	(0.503)	(0.604)
Understand stock	0.808**	0.418	1.668**	0.280
	(0.197)	(0.265)	(0.278)	(0.356)
Eco Sentiment	3.603**	2.422*	4.496**	4.866**
	(0.916)	(1.115)	(1.292)	(1.527)
Non-Eco Sentiment	3.549**	3.261*	1.554	1.061
	(1.193)	(1.364)	(1.663)	(1.861)
Num.Obs	14930	14930	13985	13985
Num.Ind	2508	2508	2483	2483
σ_u	10.318	13.635	15.961	31.876
σ_e	13.649	13.649	17.805	17.805
ρ	0.364	0.499	0.446	0.762

A constant term and time dummies are included but the coefficients are not reported to save space. ρ is the fraction of variance due to unobserved individual effect. “Num.Obs ” refers to the number of total observations. “Num.Ind ” refers to the number of individuals. Statistical significance is indicated as follows: + $p<0.10$, * $p<0.05$, ** $p<0.01$.

Table 3.19: Panel vector autoregression: additional results

	$\Delta\mu$ (1y)	$\Delta\mu$ (10y)
$\Delta\mu_{-1}$ (1y)	-0.532**	-0.015
	(0.012)	(0.019)
$\Delta\mu_{-2}$ (1y)	-0.215**	-0.003
	(0.011)	(0.017)
$\Delta\mu_{-1}$ (10y)	0.020*	-0.555**
	(0.008)	(0.013)
$\Delta\mu_{-2}$ (10y)	0.007	-0.258**
	(0.008)	(0.012)
Bachelor	0.499	0.101
	(0.342)	(0.527)
Income per capita ($1000)	-0.002	0.002
	(0.004)	(0.006)
Female	-0.255	-0.635
	(0.338)	(0.521)
Follow stock	-0.502	-0.369
	(0.355)	(0.547)
Understand stock	-0.209	-0.419
	(0.185)	(0.285)
Eco Sentiment	-0.168	1.770
	(0.968)	(1.489)
Non-Eco Sentiment	0.789	0.182
	(1.176)	(1.813)
Num.Obs	5489	5395

$\Delta\mu_{-\tau}$ refers to the $\Delta\mu$ lagged τ period. "Num.Obs " refers to the number of total observations. Statistical significance is indicated as follows: + p<0.10, * p<0.05, ** p<0.01.

Chapter 4

The Dynamics of Households' House Price Expectations

Abstract Based on monthly survey data between 2007 and 2014, this chapter studies whether and how households' house price expectations are related to experts' forecasts and perceived home value changes. We find that households follow experts when forming expectations of one-year ahead home values, and respond positively to perceived home value changes in the past. In addition, highly educated people absorb experts' house price forecasts more actively than lower educated people do.

4.1 Introduction

Households' economic expectations are important in determining future economic outcomes. The dynamics of several key macroeconomic expectations, such as inflation and unemployment expectations, have been widely investigated in the literature. The importance of expectations in the housing market is also gaining increasing recognition. House price expectations might affect households' decisions in many aspects (home purchase, consumption, mortgage default, and so forth), and influence the whole economy. For example, Miller et al. (2011) found that anticipated house price changes, as proxied by changes in home sales, can have a sizable effect on the economic productions at the metropolitan level. However, households' house price expectations are much less studied. Especially, the literature lacks studies that test models of house price expectations using data on directly observed survey expectations.

This paper attempts to fill this gap by testing one well-recognized model on households' economic expectations, developed by Carroll (2003), in the context of housing market. The model, often labeled as "epidemiological model of macroeconomic expectations", assumes that individual people form macroeconomic expectations by probabilistically absorbing the views of professional forecasters , which are spread through the news media. Individuals are also assumed to be inattentive to new information, so each period a proportion of the population will stick to expectations of the previous period. We also extend the model by including past home value changes as an additional factor that might influence expectations of future house prices. By estimating the model based on monthly expectation data from 2007 to 2014, we find that experts' forecasts positively Granger-cause households' house price expectations, both in the short-run and in the long-run. This observation is consistent with the predication by Carroll's model (Carroll, 2003). We also find that experts' forecasts and households' lagged expectations do not fully capture the dynamics of households' house price expectations, as opposed to some findings based on inflation expectations.[1] At the same time, households' expectations respond positively to their perceived changes in home values, which indicates an extrapolative element in expectations. [2] Besides, households absorb experts' forecasts heterogeneously. High-educated people follow experts' forecasts much more closely than low-educated people do. The findings in this paper are robust to the stationarity assumptions about the underlying time series.

To the best of our knowledge, this paper is the first that studies the relationship between expectations of the households and of the experts regarding future home values. The paper provides the first test of Carroll's macroeconomic expectations model in the housing market, which extends the literature to a new domain beyond inflation and unemployment expectations. More importantly, the findings shed lights on how households' house price expectations are formed. First, the positive relationship between past home value changes and future expectations suggests extrapolative behaviour in the housing market, which has long been suggested in the literature but is rarely studed using data on directly measured expectations. Notable exceptions include Piazzesi and Schneider (2009) and Case et al. (2012). Piazzesi and Schneider (2009) found that in the Michigan Survey of Consumers the fraction of people that considers it is a good time to buy a house, because house prices will increase, doubled towards the end of the housing boom. Case et al. (2012) observed that house price expectations are higher in areas and periods with higher house price appreciation rates, based on annual survey data for recent home buyers in four cities. While the above two paper are largely descriptive on this issue, this

[1] Carroll (2003) found that experts' forecasts and households' lagged expectations adequately capture households' inflation expectations in US and Doepke et al. (2008) found similar results using European data.

[2] This observation is consistent with the theory that people tend to extrapolate past trends when forming expectations of future asset prices. Based on this theory, people are overoptimistic during the booming period. This overoptimism induces people to overinvest in housing and make house prices far above the fundamentals. This is regarded as an explanation for housing booms in some literature (e.g. Case et al., 2012 and Piazzesi & Schneider, 2009). However, there are also alternative explanations for the housing bubble. One alternative is that the loosening of lending standards and supply constraints in the early 2000s raised the effective demand for housing and caused the increase in house prices, as suggested in Duca et al. (2011).

paper incorporates the potential extrapolative element into a well-established model of macroeconomic expectations and find that it still affects expectations, even after controlling for the influence of experts' forecasts. Moreover, instead of constructing past home value changes based on actual house price index, we examine the role of perceived changes based on survey questions. Second, the finding that experts' forecasts (Granger) cause the households' expectations indicate a potential role of news media in the housing market. Also, policy makers, sometimes acting as experts themselves, might be able to anchor the households' expectations. Third, the positive impact of lagged expectations on current expectations is consistent with a large body of literature stating that households are inattentive to new macroeconomic information and expectations are sticky. Inattention is considered to be able to explain several important macroeconomic phenomena, whereas its role in the housing market is not clear. Finally, the difference in the dynamics of expectations between the higher educated people and the lower educated ones suggests that the assumption of homogeneous expectations should be taken with cautions. Above all, the paper contributes to the microfoundations of how households form house price expectations, an important yet largely unexplored topic.

The paper proceeds as follows. In section 4.2, We set up a parsimonious model that describes the dynamics of households' house price expectations. Section 4.3 introduces the data. Section 4.4 provides the empirical results. Section 4.5 investigates the heterogeneity in house price expectations. Section 4.6 concludes.

4.2 A model of households' house price expectations

In this section we introduce a variation of the model on households macroeconomic expectgations in Carroll (2003). Carroll (2003) suggests that households form macroeconomic expectations by sluggishly absorbing experts' forecasts. We tailor this model to the housing market as house price expectations are also found to be related to recent house price changes (Piazzesi & Schneider, 2009 and Case et al., 2012). To be specific, we assume that the evolution of the aggregate households' τ-month-ahead house price expectations can be modeled as follows:

$$E_t^H(hg_{t,t+\tau}) = \lambda_0 + \lambda_1 E_{t-1}^H(hg_{t-1,t+\tau-1}) + \lambda_2 E_t^E(hg_{t,t+\tau}) + \lambda_3 hg_{t-\tau,t}^P + \epsilon_{\tau,t} \quad (4.2.1)$$

where $E_t^H(hg_{t,t+\tau})$ and $E_t^E(hg_{t,t+\tau})$ represent the expected τ-month growth rate in house price (hg) according to households (H) and to experts (E), respectively, and where $hg_{t-\tau,t}^P$ denotes the past τ-month change in house price perceived by households. $\epsilon_{\tau,t}$ is an identically and independently distributed idiosyncratic error term, which reflects random shocks to expectations.

The model features some well-known theories in macroeconomic expectations and incorporates both backward- and forward-looking behavior in expectations. The parameter λ_1 captures the level of the inattention effect, which says that a proportion of households does not update information and sticks to the previous period's expectations. The parameter λ_2 captures the influence of the experts' forecasts. This parameter is typically interpreted as the fraction of people that absorbs experts' forecasts each period. People are assumed to learn experts' forecasts from the news media and social interactions. Finally, the parameter λ_3 allows past house price realizations to have an impact on the expectations of the future. In particular, we assume that it is the house price change perceived by households, rather than the objective change, that plays a role, as households may not always be aware of objective measures of house prices.

Model (4.2.1) incorporates the epidemiological model of macroeconomic expectations suggested in Carroll (2003). This is the case when $\lambda_0 = \lambda_3 = 0$ and $\lambda_1 + \lambda_2 = 1$. This specific model assumes that in each period a fraction λ_2 of households forms expectations based on the experts' forecasts, while the remaining fraction λ_1 of households sticks to their own expectations in the past as it is costly to update information.

However, model (4.2.1) specifies the relationship between different time series variables in levels, which might be problematic if these variables are nonstationary. To better handle the potential nonstationarity, we further generalize model (4.2.1) into the following Vector Error-Correction Model (VECM):

$$\Delta y_t = \lambda \alpha' y_{t-1} + \beta(L)\Delta y_t + \epsilon_t, \tag{4.2.2}$$

where $y_t = (E_t^H(hg_{t,t+\tau}), E_t^E(hg_{t,t+\tau}), hg_{t-\tau,t}^P)'$ denotes the vector of endogenous variables, Δ denotes the first-different operator, $\lambda = (\lambda_H, \lambda_E, \lambda_P)'$ and $\alpha = (\alpha_H, \alpha_E, \alpha_P)'$ are vectors of unknown parameters related to the long-run equilibrium, and $\beta(L)$ denotes a matrix of coefficients related to the short-run dynamics. To be specific, the vector α describes the long-run relationship between the (endogenous) variables and λ describes the speed of adjustment towards the long-run relationship. In this error correction form, the epidemiological model of macroeconomic expectations in Carroll (2003) would imply a cointegrating vector $\begin{pmatrix} 1 & -1 & 0 \end{pmatrix}'$. In such a case, the households' expectations fully adapt to the experts' forecasts in the long-run.

Apart from taking into account nonstationarity, model (4.2.2) generalizes model (4.2.1) in several ways. First, model (4.2.2) does not predetermine which variable is exogenous and allows variables in the system to affect each other. This might be relevant if, for example, the households' expectations can have feedback effects on the experts' forecasts. Second, model (4.2.2) distinguishes between the short-term dynamics, as captured by the first differences terms, and the long-term relationship, as represented by the cointegration relationship.

The error-correction model (4.2.2) also allows us to test the existence and direction of (Granger) causality. From equation (4.2.2), the dynamics of a certain variable $y_{i,t}$ in the vector y_t can be represented as

$$\Delta y_{i,t} = \lambda_i \alpha' y_{t-1} + \sum_{\tau=1}^{q} \beta_{i,\tau} \Delta y_{i,t-\tau} + \sum_{\tau=1}^{q} \beta_{j,\tau} \Delta y_{j,t-\tau} + \sum_{\tau=1}^{q} \beta_{k,\tau} \Delta y_{k,t-\tau} + \epsilon_{i,t}, \quad (4.2.3)$$

where $y_{j,t}$ and $y_{k,t}$ are the other two variables in the vector y_t. There are potentially two sources of (Granger) causality in equation (4.2.3). First, joint significance of $\beta_{j,\tau}$-s would indicate that the dependent variable $y_{i,t}$ responds to short-term shocks to the variable $y_{j,t}$, which can be interpreted as short-term Granger causality from $y_{j,t}$ to $y_{i,t}$. This hypothesis can be evaluated using a Wald test. Second, significance of λ_i would indicate that the dependent variable $y_{i,t}$ is driven by the long-run equilibrium relationship, which can be interpreted as long-run Granger causality from $\alpha' y_{t-1}$ to $y_{i,t}$. This hypothesis can be evaluated by a t-test.[3]

4.3 Data

4.3.1 Expectations of households

House price expectations are not regularly asked in major US household surveys starting until the recent housing burst. We obtain households' house price expectations from the Michigan Surveys of Consumers, which covers the longest time span.[4] The Michigan survey is a monthly survey of approximately 500 randomly chosen individuals and is representative of the U.S. adult population. In January 2007, this survey added a question about expected changes in home values, which reads: "By about what percent do you expect prices of homes like yours in your community to go (up/down), on average, over the next 12 months?" To examine the representativeness of the expectation data in the Michigan survey, we also uti-

[3] See, for example, Kleibergen and van Dijk (1994), Oh and Lee (2004), and Soytas and Sari (2003) for the concept and application of Granger causality in error correction models.

[4] Case and Shiller began to survey house price expectations from the late eighties. However, their sample only includes recent home buyers in four cities and the frequency is annual. Thus, the data is not approximately for a rigorous time-series analysis of national house price expectations.

lize data in the Fannie Mae National Housing Survey, which covers a shorter time period. From June 2010 on, in each month Fannie Mae surveyed a random sample of approximately 1,000 Americans, who also represent the U.S. adult population. One of the survey questions asks about expected one-year changes in general house prices, which reads: "By about what percent do you think home prices in general will go (up/down) on average over the next 12 months?" The time pattern of the general house price expectations from the Fannie Mae survey is quite similar to the time pattern of the home value expectations from the Michigan survey. See section 4.4.1 for details.

4.3.2 Expectations of experts

We obtain experts' forecasts of future house prices from the Wall Street Journal economic forecasting survey (WSJ survey). This survey collects and reports predictions of several U.S. macroeconomic variables from a group of professional forecasters. The survey results are published online regularly. From late 2006, on a monthly basis (with some gaps), the WSJ survey asks around 50 forecasters to predict the annual percentage change in the U.S. Federal Housing Finance Agency (FHFA) house price index over the current and the next calendar year.[5]

In each month the WSJ survey contains a pair of forecasts, $E_t^E(hg_{t,t+s})$ and $E_t^E(hg_{t,t+12+s})$, where $s \in \{1, 2, \ldots, 12\}$ is the number of months to the end of the current year.[6] Thus, for a given year the forecast horizon varies from month to month as the forecast target is fixed. To match the data to the expectations in the household surveys mentioned above, we transform the WSJ survey predictions into fixed-horizon (one-year-ahead) forecasts. To be specific, we construct the expected housing return in one year as a weighted average of the forecasts of the current and

[5] See Zhang (2013) for a recent work that also uses the WSJ house price forecast data.

[6] The value of s depends on the month of time t. For example, if the month of time t is January, $s = 12$.

the next year's housing return. To be specific, $E_t^E(hg_{t,t+12})$ is constructed as follows:

$$E_t^E(hg_{t,t+12}) = \frac{s}{12}E_t^E(hg_{t,t+s}) + \frac{12-s}{12}E_t^E(hg_{t,t+12+s}).$$

This method to transform fixed-event forecasts into fixed-horizon forecasts follows a standard practice in the literature. For example, Dovern et al. (2012) use this method to construct fixed-horizon GDP growth and interest rates predications, and Easaw et al. (2013) use this method to study the influence of experts' forecasts on households' inflation expectations.

4.3.3 Perceived changes in home values

We derive households' perceived changes in home values from the Michigan survey. This means that the perceived and expected changes in home values investigated in this paper are from the same group of people. The following question is asked in the Michigan survey:

> Do you think the current value of your home–I mean, what it would bring if you sell it today–has increased compared with a year ago, has decreased compared with a year ago, or has it remained about the same?

An aggregate index of perceived home value change based on responses to the above question is constructed by the Michigan survey center according to the formula:

$$Perceived\,home\,value\,change = 100 + up - down$$

where "up", and "down" denote the percentage of individuals reporting increased and the percentage responding decreased, respectively. In addition, to make the magnitudes of the perceived and expected changes comparable, we rescale the index of the perceived home value change according to the 12-month growth rates in the national house price index of the Federal Housing Finance Agency.

4.4 Empirical results

4.4.1 Time patterns of the underlying time series

Figure 4.1 presents the time patterns of the underlying time series. In panel (a), it can be seen that the two series of households' expectations, namely, the one from the Michigan survey and the one form the Fannie Mae survey, are quite similar. The aggregated home value expectations in the Michigan survey closely approximate the general house price expectations.[7] Henceforth, we only use expectations from the Michigan survey in my analysis and refer to this series as "Households' expectations", given its longer time period. The time pattern of the experts' forecasts, shown in panel (b), looks also similar to the one of the households' expectations. In general, one-year house price expectations kept declining during the financial crisis, rebounded temporally between 2009 and 2010, and started to recover after bottoming at the end of 2011. The dynamics of the perceived home value changes, plotted in panel (c), show a similar pattern. For comparison, panel (d) depicts the 12-month percentage changes of the Case-Shiller national Home Price index during the sample period, which are very similar to the perceived home value changes over time.

4.4.2 Stationarity tests

As a first step in the econometric analysis, we test all variables for stationarity. We apply different tests and the results are summarized in table 4.1. The null hypothesis in each test is that the variable contains a unit root. "ADF" refers to the Augmented Dickey-Fuller test (Dickey & Fuller, 1979), "DF-GLS " refers to a modified version of the Dickey-Fuller test that detrends the series by generalized least squares (Elliott et al., 1996), and "Phillips-Perron" refers to the Phillips-Perron test which controls for serial correlation using Newey-West standard errors (Phillips & Perron, 1988).

[7]For the Fannie mae survey only the aggregated level data are publicly available.

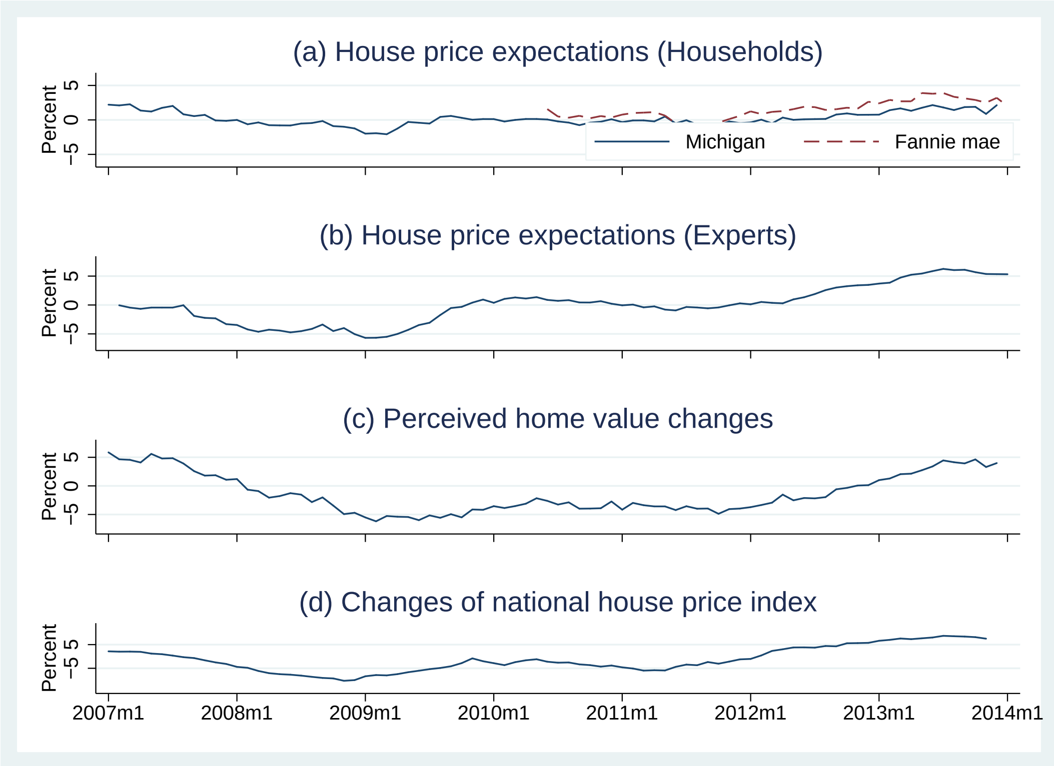


Figure 4.1: Time patterns of house price expectations and home value changes

Phillips and Perron (1988) provide two test statistics, which correspond to the τ test and the ρ test in table 4.1, respectively. Each unit root test is performed with and without including a time trend. The test results do not reject the null of a unit root. However, my sample might not be long enough to make conclusive inference as unit root tests in general lack power in small samples. We take this issue into account by estimating model (4.2.1) under different stationarity assumptions.

4.4.3 Empirical results based on the time series in levels

Although We cannot reject the existence of a unit root in the underlying time series, we begin with estimating model (4.2.1) using data in levels for several reasons. First, unit root tests are found to lack power in small samples. Thus, the test results in section 4.4.2 might not be conclusive. Second, even if the time series are not stationary, the coefficients can still be consistent if the time series are cointegrated. Third, it is easier to compare the results from model (4.2.1) to the previous literature

Table 4.1: Unit root tests

Method	Households		Experts		Home value changes	
	Statistic	5% CV	Statistic	5% CV	Statistic	5% CV
Without a time trend						
ADF	-2.516	-2.908	-1.176	-2.910	-1.322	-2.906
DF-GLS	-1.286	-2.181	-1.297	-2.132	-0.908	-2.129
Phillips-Perron (τ test)	-9.547	-13.532	0.283	-13.532	-3.133	-13.532
Phillips-Perron (ρ test)	-2.524	-2.907	0.127	-2.907	-1.398	-2.907
With a time trend						
ADF	-2.870	-3.473	-3.118	-3.475	-0.274	-3.470
DF-GLS	-1.293	-3.096	-2.218	-3.043	-1.107	-2.811
Phillips-Perron (τ test)	-8.941	-20.322	-5.685	-20.304	-0.680	-20.340
Phillips-Perron (ρ test)	-2.585	-3.471	-1.956	-3.472	-0.384	-3.470

The number of lags in the ADF test and the DF-GLS test are selected based on BIC and Ng-Perron MAIC, respectively. "CV" refers to the critical value.

on households' macroeconomic expectations, as Carroll's original model (Carroll, 2003) and many other models of inflation expectations are estimated using data in levels. However, the results in this section are in general illustrative and should be interpreted with caution. A more rigorous analysis is presented in section 4.4.4.

Table 4.2 presents the estimation results of some variations of model (4.2.1). The first variation (M1) includes only the lagged households' expectations and experts' forecasts, both of which are statistically significant with a positive sign. However, the sum of the two coefficients are significantly below one.[8] Thus, Carroll's epidemiological model (Carroll, 2003) does not seem to capture adequately the dynamics of house price expectations. The second variation (M2) includes the lagged households' expectations and households' perceived house price changes, showing that expectations are positively related to home value changes. The third one (M3) includes both experts' opinions and perceived house price changes as regressors. The results indicate that when forming expectations of future home values, households in part learn from experts and in part extrapolate past house prices. In all specifications the coefficient of the lagged expectation variable is always the largest. A possible inter-

[8] A Wald test is performed but the results are not shown to save space.

pretation is that in each period a large fraction of households is inattentive to new information and sticks to the expectations at the previous period. This phenomenon is widely documented for households' macroeconomic expectations. Model 4 adds the actual 12-month home value growth rate, based on the Case-Shiller national home value index, as an additional regressor. Its coefficient turns out to be neither economically nor statistically significant. This is consistent with the assumption that the perceived home value changes, rather than the actual movements of the house prices, influence future expectations. Given that the two series are also highly correlated, hereafter we will only use the perceived home value changes in the analysis. We also test whether the residuals are stationary in each specification, following the cointegration method in Engle and Granger (1987) to take into account the non-standard test statistics. The test statistics, reported in the last row of table 4.2, indicate that the residual series are stationary in each specification. However, there is no particular reason to specify the households' expectations as the only exogenous variable. In the following sections we focus on vector error correction models, which do not restrict the direction of causality ex ante.

4.4.4 Estimation results in a Vector Error-Correction form

As discussed in section 4.2, a Vector Error-Correction model is better suited at handling the potential nonstationarity and endogeneity problems. In this section we will present the estimation results based on model (4.2.2). We first examine the number of cointegration relationships in the system based on the Johansen cointegration test (Johansen, 1991). Table 4.3 shows the test results. The null of no cointegration and the null of one cointegration relationship are both rejected while the the null of two cointegration vectors are not rejected. Thus, we proceed under the assumption of two cointegration vector.

The estimation results of the VECM (4.2.2) are shown in table 4.4. As cointegration vectors in a VECM are not determined without restrictions, we normalize

Table 4.2: Estimation results of model (4.2.1)

	Model 1	Model 2	Model 3	Model 4
Lagged Households' Exp.	0.73**	0.62**	0.41**	0.45**
	(0.07)	(0.09)	(0.10)	(0.10)
Experts' Exp.	0.07**		0.08**	0.08*
	(0.02)		(0.02)	(0.04)
HomeValueChange (perceived)		0.09**	0.11**	0.10**
		(0.03)	(0.03)	(0.03)
HomeValueChange (actual)				-0.01
				(0.03)
constant	0.03	0.17*	0.21**	0.18**
	(0.05)	(0.07)	(0.06)	(0.07)
Num.Obs	83	83	83	82
R^2	0.802	0.798	0.836	0.836
adj. R^2	0.797	0.793	0.830	0.828
H_0: Non-stationary residuals	-7.5**	-5.5**	-6.2**	-4.6*

"Num.Obs" refers to the number of total observations. Statistical significance is indicated as follows: + p<0.10, * p<0.05, ** p<0.01. The last row shows the the test statistics for the Engle-Granger cointegration tests.

Table 4.3: Johansen cointegration test

H_0	Eigenvalue	Trace	1% CV	Max-eigen	1% CV
rank=0	0.326	55.50	35.65	33.42	25.52
rank≤1	0.214	22.07	20.04	18.19	18.63
rank≤2	0.053	3.87	6.65	3.87	6.65

Variables in the system: households' expectations, experts' expectations, and households' perceived home value changes. Number of lags is selected based on BIC. "Trace" refers to the trace statistics, "Max-eigen" maximum-eigenvalue statistic, and "CV" refers to the critical value.

the coefficient in front of Households' expectations to be unity in each cointegration vector. The number of lags in first-differences is selected according to the BIC criterion.

The first cointegration vector, describing the relationship between households' expectations and experts' forecasts, suggests that the two series are positively related to each other in the long-run. Again, this finding is in the spirit of the model about households' macroeconomic expectations in Carroll (2003). However, the cointegration vector ($\begin{pmatrix} 1 & -0.49 & 0 \end{pmatrix}'$) indicates that the correspondence between the households' expectations and the experts' forecasts is not one-to-one in the long-run. The second cointegration vector describes the relationship between households' expectations and their perceived home value changes in the long run, which turn out to be also positive. To be specific, above one quarter of the change in the perceived home values is transmitted to the expectations.

Let us now turn to the loading parameters. For the first cointegration vector, the loading parameter (λ) in front of the households' expectations is significantly negative while the one in front of the experts' forecasts is not significant. This suggests that the households adjust expectations towards the experts' forecasts. This can also be interpreted as the experts' forecasts Granger-cause the households' expectations in the long run, but not vice versa. In addition, the households' perceived home value changes are also affected by the first cointegration vector, as the corresponding loading parameter is significantly negative. One potential reason for this is that the households' perceived home values changes are influenced by news in the media, which might be positively correlated to the experts' expectations. For the second cointegration vector, the loading parameters in front of the households' expectations and home value changes are both significantly negative, indicating that there exists bidirectional causality between the two series. Besides, the experts' forecasts also influence the households' expectations positively in the short-run, evidenced by the relevant coefficients in the lag polynomial of the first-differenced terms. Finally,

Table 4.4: Estimation results of Vector Error-Correction model (4.2.2)

Cointegration equation	Households' Exp.	Experts' Exp.	HomeValue Change
CE1	1	-0.4421**	0
		(0.064)	
CE2	1	0	-0.274**
			(0.024)
	Δ Experts' Exp.	Δ HomeValueChange	Δ Households' Exp.
Loading parameters (CE1)	-0.017	-0.244**	-0.211**
	(0.063)	(0.079)	(0.053)
Loading parameters (CE2)	0.231+	0.376*	-0.332**
	(0.128)	(0.161)	(0.109)
Lag Δ Experts' Exp.& 0.061	0.330*	0.273*	
	(0.128)	(0.160)	(0.108)
Lag Δ HomeValueChange	-0.025	-0.388**	-0.145*
	(0.087)	(0.109)	(0.073)
Lag Δ Households' Exp.	0.105	-0.110	-0.082
	(0.150)	(0.189)	(0.127)
Num.Obs	81	81	81
LM test for residual autocorrelation (P-value)			
AR(1)		0.597	
AR(6)		0.884	

"CE1" and "CE2" refer to the first and second cointegration vectors, respectively. "Num.Obs" refers to the number of total observations. Statistical significance is indicated as follows: + $p<0.10$, * $p<0.05$, ** $p<0.01$.

we do not find that the residuals are autocorrelated, indicating that the Vector Error-Correction model we estimated seems to be appropriate.

4.5 Heterogeneous dynamics of house price expectations

While so far we have found that households as a whole follow experts when forming house price expectations, we have not investigated the potential heterogeneity across households, which has been documented in the previous literature with regard to other macroeconomic expectations. For example, Easaw and Roberto (2010) have shown that some groups of people more actively absorb professional forecasters' inflation expectations than some other groups. Similarly, Pfajfar and Santoro (2013) found that not all households in the Michigan survey adjust inflation expectations towards experts' predictions.

Motivated by these finding, in this section we investigate the possible heterogeneity in the way households absorb experts' house price forecasts. We use the education level to classify respondents in the Michigan survey into two groups, those with bachelor degrees (the high-educated) and those without (the low-educated), and average the house price expectations of the two groups over time, respectively. We choose education level as the group identifier since education might be related to the way information is processed. It is indeed found in the previous literature that, for example, higher-educated people follow experts more closely when forming inflation expectations (Easaw et al. (2013)).

4.5.1 Bivariate VECM

Now there are three time series of expectations, one from the experts, one from the high-educated people, and one from the low-educated people. We begin with examining the piecewise relationship between each pair of expectation series through the following bivariate VECM:

$$\begin{bmatrix} \Delta E_t^i(hg_{t,t+12}) \\ \Delta E_t^j(hg_{t,t+12}) \end{bmatrix} = \begin{bmatrix} \alpha_i \\ \alpha_j \end{bmatrix} \begin{bmatrix} 1 \; \beta \end{bmatrix} \begin{bmatrix} E_{t-1}^i(hg_{t-1,t+11}) \\ E_{t-1}^j(hg_{t-1,t+11}) \end{bmatrix} \tag{4.5.1}$$

$$+ \sum_{\tau=1}^{q} B_\tau \begin{bmatrix} \Delta E_{t-\tau}^i(hg_{t-\tau,t-\tau+12}) \\ \Delta E_{t-\tau}^j(hg_{t-\tau,t-\tau+12}) \end{bmatrix} + \begin{bmatrix} \epsilon_t^i \\ \epsilon_t^j \end{bmatrix} \tag{4.5.2}$$

where $E_t^i(hg_{t,t+12})$ ($E_t^i(hg_{t,t+12})$) is the 12-month-ahead house price expectations from group i (j). The cointegration relationship is normalized for group i.

Here we start with the bivariate cointegration analysis rather than a multivariate cointegration analysis that includes all the three time series simultaneously. This is mainly because that the number of observations is limited and including too many

Table 4.5: Cointegration tests for bivariate VECMs

Experts and high-educated people				
H_0	Trace	5% CV	Max-eigen	5% CV
rank=0	19.84	15.41	19.82	14.07
rank≤1	0.02	3.76	0.02	6.65
Experts and low-educated people				
H_0	Trace	5% CV	Max-eigen	5% CV
rank=0	12.61	15.41	12.60	14.07
rank≤1	0.02	3.76	0.02	6.65
high-educated and low-educated people				
H_0	Trace	5% CV	Max-eigen	5% CV
rank=0	21.79	15.41	18.90	14.07
rank≤1	2.89	3.76	2.89	6.65

Number of lags is selected based on BIC. "Trace" refers to the trace statistics, "Max-eigen" maximum-eigenvalue statistic, and "CV" refers to the critical value. Statistical significance is indicated as follows: + p<0.10, * p<0.05, ** p<0.01.

variables reduces the degrees of freedom in the estimation of an error correction model. Moreover, the inclusion of too many variables also makes it difficult to give economic meaning to the estimated cointegration results as the choice of normalization is arbitrary. Thus, the results of the bivariate cointegration analysis in this section will be complementary to the multivariate cointegration analysis in the next section.

Table 4.5 presents the results of Johansen cointegration test (Johansen, 1991) for the bivariate system (4.5.1) with regard to each pair of expectation series, respectively. The null of no cointegration is rejected at the 5 % significance level for the pair including the experts and the high-educated people, as well as the pair including the high-educated and the low-educated people. In contrast, the null that there is no cointegration between expectations from the low-educated people and the experts' forecasts is not rejected. These results already indicate that the high-educated people and the low-educated people perceive experts' forecasts differently.

Table 4.6 shows the estimated bivariate cointegration vectors for each pair of expectations.[9] The result indicates that there is a positive, though less than one-to-

[9] Although the null of no cointegration between the low-educated peole' expectations and the experts' forecasts is not rejected at the 5 % significance level, for the sake of completeness, we still

Table 4.6: Bivariate cointegration relationships

Low-educated	High-educated	Experts
	1	−0.298**
		(0.038)
1		−0.159*
		(0.067)
1	−0.668**	
	(0.113)	

Statistical significance is indicated as follows: + p<0.10, * p<0.05, ** p<0.01.

one, relationship between house price expectations from different groups of people. The cointegration vector in the first row indicates that in the long run 30% of the experts' forecasts are absorbed by high-educated people, which is more than double the absorption rate of the low-educated people (14.7%) shown in the second row. Finally, the third row of the table suggests that the house price expectations between the high-educated and the low-educated people are highly correlated in the long term. Although the above comparisons have not fully taken into account the interactions among all the three groups of expectations together, which will be investigated in the multivariate analysis in the next section, the results provide suggestive evidence that the long-run relationship between forecasts from the experts and those from the low-educated people is the weakest.

To see the direction of causality, table 4.7 shows the loading parameters for the bivariate cointegration vectors in system (4.5.1). Each figure in the table corresponds to a loading parameter for a bivariate cointegration relationship between the group of people indicated by the row name and the group indicated by the column name. For each cointegration vector, the figure above the diagonal refers to the estimated loading parameter α_i in the VECM (4.5.1), whose cointegration relationship is normalized for group i in the row. The corresponding figure below the diagonal is the estimated parameters α_j of the same VECM. The results in the last row show that

show the estimated VECM parameters for this pair. Moreover, as cointegration tests lack power in small samples and the test statistic for the pair including the low-educated people and the experts is close to the 10 % significance level, a cointegration relationship may still exist.

Table 4.7: Estimated loading parameters in bivariate VECMs

Group	Low-educated	High-educated	Experts
Low-educated		−0.498**	−0.313**
High-educated	−0.020		−0.436**
Experts	−0.069	−0.107	

Each figure in the table corresponds to a loading parameter for a bivariate cointegration relationship between the group of people indicated by the row name and the group indicated by the column name. For each cointegration vector, the figure above the diagonal refer to the estimated loading parameter α_i in the VECM (4.5.1), whose cointegration relationship is normalized for group i in the row. The corresponding figure below the diagonal is the estimated parameter α_j of the same VECM. Statistical significance is indicated as follows: + p<0.10, * p<0.05, ** p<0.01.

experts' forecasts are always weakly exogenous, in the sense that the corresponding loading parameter is never significant. The results can also be interpreted as experts' forecasts Granger cause expectations of other groups of people, but not vice versa. On the contrary, the results in the first row indicate that when expectations from the low-educated people are part of a VECM, the error-correction process is always driven by the adjustment in their expectations rather than expectations of another group. The results in the second row suggest that expectations from the high-educated people follow the experts' forecasts and are followed by expectations from the low-educated people. Furthermore, the high-educated people also follow the experts more closely than the low-educated people do, as evidenced by the magnitudes of the corresponding loading parameters (−0.425 for the former and −0.292 for the latter).

4.5.2 Multivariate analysis

To further investigate the relationship among expectations from different groups, we resort to a multivariate analysis in this section. We first test the number of cointegration vectors in the three expectations series, the results of which are shown in table 4.8. The null of no cointegration relationship is rejected. The null of one cointegrations vector cannot be rejected at the 5% significance level for the trace test but can be rejected for the maximum eigenvalue test. The null of two cointegrations

Table 4.8: Tests of cointegration ranks in three expectation series

H_0	Trace	5% CV	Max-eigen	5% CV
rank=0	49.81	29.68	34.80	20.97
rank≤1	15.01	15.41	14.99	14.07
rank≤2	0.022	6.65	0.022	6.65

Variables in the system: households' expectations, experts' expectations, and households' perceived home value changes. Number of lags is selected based on BIC. "Trace" refers to the trace statistics, "Max-eigen" maximum-eigenvalue statistic, and "CV" refers to the critical value.

vectors cannot be rejected for both tests. According to the sequential testing rule suggested in Johansen (1992), the trace test results would imply the existence of one cointegration relationship while the maximum eigenvalue test results would imply two cointegration vectors. Here we assume that there exists two cointegration vectors in the system for several reasons. First, if we hold the assumption in the previous bivariate analysis that any two among the three expectation series are cointegrating, theoretically there should exist two cointegration vectors in the multivariate system (Hall et al., 1992). Second, the trace test comes very close to reject the null of only one cointegration vector at the 5% significance level. Third, the Schwarz Bayesian information criterion (SBIC) is 4.78 for the model with one cointegration vector and is 4.76 for the model with two cointegration vectors, supporting the latter model.

Next, we estimate a multivariate VECM including expectation series from all the three groups. To identify the parameters the following normalization restrictions are imposed: The first cointegration relationship contains expectations from the two groups of households where the coefficient in front the low-educated people's expectations is one; The second cointegration relationship contains expectations from the high-educated people and from the experts where the coefficient in front the former is one. These restrictions are motivated by the findings in the bivariate analysis that the relationship between the low-educated people's expectations and the experts' forecasts is rather weak.

The estimated cointegration vector and loading parameters are shown in table 4.9. The estimated cointegration relationships are similar to those obtained in the

Table 4.9: Multivariate error correction models

Cointegration equation	Low-educated	High-educated	Experts
CE1	1	-0.523**	0
		(0.102)	
CE2	0	1	-0.302**
			(.034)
	Δ Experts' Exp.	Δ High-edu' Exp.	Δ Low-edu' Exp.
Loading parameters (CE1)	-0.038	0.199+	-0.629**
	(0.120)	(0.121)	(0.141)
Loading parameters (CE2)	-0.077	-0.542**	0.208
	(0.117)	(0.118)	(0.137)
Num.Obs	81	81	81

"CE1" and "CE2" refer to the first and second cointegration vectors, respectively. "Num.Obs" refers to the number of total observations. Statistical significance is indicated as follows: + p<0.10, * p<0.05, ** p<0.01.

bivariate analysis in section 4.5.1. To be specific, the first cointegration vector suggests that expectations from the two groups of households are positively related in the long run, which can be compared to the third row in table 4.6; the second cointegration vector implies that the high-educated people's expectations and the experts' forecasts are positively linked, which can be compared to the first row in table 4.6.

Turning to the loading parameters. First, the loading parameters in front of the experts' forecasts are insignificant for both cointegration vectors, indicating that this variable is weakly exogenous in the system. For the first cointegration vector, the loading parameter in front of the low-educated peoples' expectations is negatively significant at the 1% level while the one in front of the high-educated people is only significant at the 10% level, suggesting that the former group follows the latter group. For the second cointegration vector, the loading parameter in front of the high-educated peoples' expectations is negatively significant at the 1% level, which indicates that this group of people follows the experts. Besides, the expectations of the low-educated peoples are hardly affected by the second cointegration vector, as the corresponding loading parameter is only significant at the 10% level, which implies that in general they do not directly follow the experts when forming expectations.

The results from both the bivariate and the multivariate analysis suggest that, when forming house price expectations, high-educated people follow experts' forecasts more closely compared to low-educated people. This finding is consistent with the previous literature on households' inflation expectations (Easaw et al., 2013). One explanation is that high-educated people in general have better access to the news media and are more willing to absorb macroeconomic news, which reflects experts' forecasts. Besides, this group of people is also more likely to encounter experts via social interactions.

4.6 Conclusion

This paper studies the dynamics of households' house price expectations during and after the financial crisis, based on survey data that are available only recently. The paper contributes new empirical findings on households' macroeconomic expectations in general, and house price expectations in particular. We show that households' house price expectations are influenced positively by both experts' forecasts and past home value changes. Besides, high-educated people are more active in absorbing experts' forecasts than low-educated people and low-educated people also follow the high-educated when forming expectations.

There is literature arguing that some deviations from rational expectations are necessary to understand the movements of house prices, especially the bubble and burst. This paper tests one alternative model of macroeconomic expectations in the housing market. The results suggest that models on formations of house price expectations might incorporate features such as extrapolative behaviour, the influence of news media, the inattention of households, and heterogeneous dynamics between socio-economic groups. Some of the features, such as the role of news media and social interactions, can be addressed more directly if data are available. Besides, the empirical findings only partly support Carroll's model. The households' expectations do not fully correspond to the experts' forecasts in the long-run. There might exist some unique features regarding house price expectations, which are worth investigating.

From a practical point of view, experts' forecasts can potentially serve as early signals to monitor house price expectations of the whole population. Besides, the expects' forecasts about macroeconomic variables are on average better than the household' own expectations.[10]. The policy makers might want to anchor households' house price expectations for the sake of financial stability. We find that although households follow experts' forecasts, the absorbing rate seems to be rather low. Thus, more effective communication is required, especially towards the low-educated people.

[10]This has been documented in for example inflation expectations. Recently, Zhang (2013) analyzed the experts' forecast of future house prices in the WSJ survey, and found that most of the forecasts are unbiased.

Appendix

4.7 Lagged experts' forecasts

Model (4.2.1) includes the households' expectations and the experts' forecasts in the same month, which follows the settings in related literature on inflation expectations (e.g. Carroll, 2003, Doepke et al., 2008, and Easaw et al., 2013). One concern is that the households might not be aware of the experts' forecasts in the current month. To address this issue, we replace the experts' forecasts with their forecasts in the previous month in model (4.2.1). The estimation results with lagged experts' forecasts are shown in table 4.10. The coefficients are very similar to the ones in table 4.2. Thus, the conclusion does not change if we use lagged experts' forecasts.

Table 4.10: Estimation results of model (4.2.1) using lagged experts' forecasts

	Model 1	Model 2	Model 3	Model 4
Lagged Households' Exp.	0.72**	0.62**	0.42**	0.48**
	(0.07)	(0.09)	(0.10)	(0.10)
Experts' Exp.	0.07**		0.08**	0.03
	(0.02)		(0.02)	(0.04)
HomeValueChange (perceived)		0.09**	0.10**	0.07*
		(0.03)	(0.03)	(0.03)
HomeValueChange (actual)				0.03
				(0.02)
constant	0.03	0.17*	0.20**	0.17*
	(0.05)	(0.07)	(0.07)	(0.07)
Num.Obs	82	83	82	81
R^2	0.785	0.798	0.817	0.820
adj. R^2	0.779	0.793	0.810	0.811

"Num.Obs" refers to the number of total observations. Statistical significance is indicated as follows: + p<0.10, * p<0.05, ** p<0.01.

4.8 Impulse response analysis

In this section we perform some impulse response analysis regarding the vector error-correction model (4.2.2), based on the estimation results shown in table 4.4.

Panel (a) of figure 4.2 shows that the households' expectations raise to a new level permanently in response to a positive innovation in the experts' forecasts. This is consistent with the fact that there is a positive long-run relationship between the two series and the experts' forecasts Granger-cause the households' expectations. Panel (b) shows the impact of an innovation in the perceived home value changes on the households' future expectations, which is also positive but of a lower magnitude. Panel (c) and panel (d) show the influence of innovations in the households' expectations, which in general die off quickly.

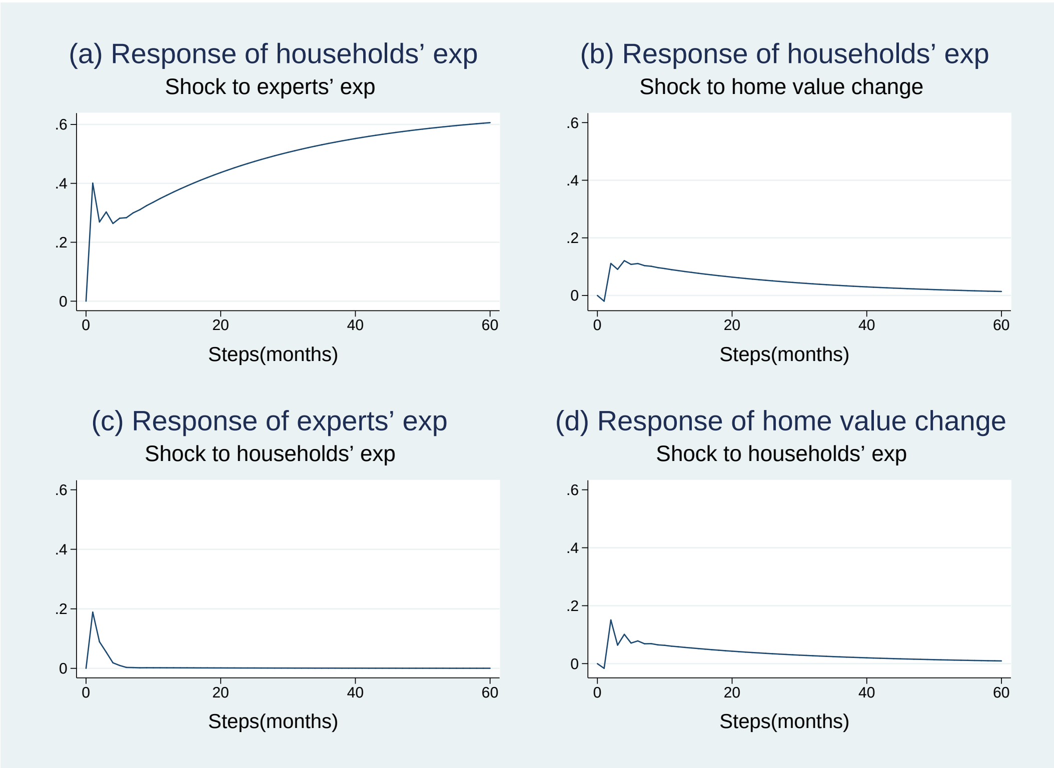


Figure 4.2: Impulse Response Analysis

Chapter 5

Trends in Mortality Decrease and Economic Growth

[Based on joint work with Bertrand Melenberg: Niu, G., & Melenberg, B. (2014). Trends in Mortality Decrease and Economic Growth, *Demography*, forthcoming.]

Abstract The vast literature on extrapolative stochastic mortality models mainly focuses on the extrapolation of past mortality trends and summarizes the trends by one or more latent factors. However, the interpretation of these trends is typically not very clear. On the other hand, explanation methods are trying to link mortality dynamics with observable factors. This chapter serves as an intermediate step between the two methods. We have performed a comprehensive analysis on the relationship between the latent trend in mortality dynamics and the trend in economic growth represented by GDP. Subsequently, the Lee-Carter framework is extended through the introduction of GDP as an additional factor next to the latent factor, which provides a better fit and better interpretable forecasts.

5.1 Introduction

The twenty century has seen a remarkable increase in average human lifetime compared to previous centuries. For most developed countries, mortality rates have fallen dramatically at all ages. By the beginning of the twenty-first century, the average life span has reached about 70 years, while in the middle of the twenty century the number was between 60 and 65 years and in the middle of eighteenth century the number was around 40 to 45 years. The average lifetime among early humans was considered to be between 20 and 30 years, as suggested by archaeological evidence. Roughly speaking, the average life span increased by 25 years in the 10,000 years before the middle of eighteenth century and increased by another 25 years between the end of eighteenth century and the twenty century century. The recent longevity improvement is rather impressive. For more details of the mortality trend, see, for example, Pitacco et al. (2009).

The fast increase of longevity is accompanied by an increasing attention on risk management for insurance companies and pension funds. For example, the Solvency slowromancapii@ project, which aims at redesigning financial regulation of insurance companies in Europe, imposes a risk-based capital requirement. The tightening of regulation and supervision makes longevity risk a significant factor related to the sustainability of pensions and insurance companies, as well as the whole society.

In response to the increasing role of longevity risk and the demand for more accurate projections of future mortality rates, a vast literature on mortality forecasting has been produced during the recent decade. The mortality forecasting methods can be divided into three categories, see Booth and Tickle (2008): expectation, extrapolation, and explanation. The expectation method is based on expert opinions, the explanation method tries to link mortality dynamics to some risk factors, and the extrapolation method assumes that past mortality trends will continue in the future.

Most of the models lie in the category of extrapolation. In general, these models focus on the historical mortality changes, and extract some latent factors from historical data. In general, each latent factor summarizes a trend in mortality rates along some dimension, for example, period or cohort. However, how these trends will behave in the future is hard to determine, as long as it is not fully understood what kind of forces are behind them. Most studies focus on an ARIMA modeling of these latent factors; only few have confronted them with some observable socio-economic variables. In contrast, we try to examine and understand the latent trends in mortality in terms of observable trends. One of the well observed and heavily studied trends, accompanying the mortality decline in recent centuries, is the rapid growth in output.[1] This comovement, which clearly seems to last for centuries, is not likely to be a coincident, not to mention the widely documented role of economic growth on the long-term mortality decline (see, for example, Brenner (2005)). Even if there is not a strong direct link between mortality rates and economic levels, the trends in the two series might be affected by some similar underlying factors and are bundled in the long-term.

The main goal of this paper is to examine the "equilibrium" relationship between the trend in mortality and the trend in economic growth. In the first part of this paper, we investigate to what extent the trend in mortality, as quantified by the Lee and Carter (1992) model, is captured by the trend in economic growth, as represented by real GDP. More specifically, using data from 1950 to 2007 of six OECD countries, namely, the United States, the United Kingdom, the Netherlands, Canada, Australia, and Japan, the first part of the paper compares the latent factor of the Lee-Carter model with real GDP per capita. Here, the main findings are: First, Johansen cointegration tests indicate that the two series have a long-run relationship. Second, the two series have comparable performance in terms of fitting historical mortality rates. Third, the two series imply similar mortality projections. In short, the real GDP series is qualified to be a substitute for the latent factor in the

[1] See the section "Economic growth and mortality rates" for an overview of related literature.

Lee-Carter model. This part of our paper is most closely related to Hanewald (2011). She mainly studies the relationship between mortality rates and the fluctuations in macroeconomics, while we present a comprehensive analysis on the trends, which can be associated with the long-term dynamics of these series.

Based on these findings, we propose a stochastic mortality model that includes both latent and observable factors, which aims at better interpreting and predicting mortality dynamics. Forecasting mortality rates is a natural application of our model. Our mortality forecasting method can be seen as a combination of the explanation and extrapolation methods in Booth and Tickle (2008). Firstly, from the perspective of explanation methods, we include real GDP per capita as an observable factor, witch captures the correlation between long term trends in mortality dynamics and economic growth. Secondly, from the perspective of the extrapolation methods, our model captures the trend in mortality rates and forecast future mortality rates based on historical trends. The results from applying the model to our sample data show that, compared to the original Lee-Carter approach, the proposed model fits the data better.

5.2 Literature Review

5.2.1 Extrapolative mortality modeling

One of the most well-know extrapolative mortality models is the Lee and Carter (1992) model (hereafter referred to as “Lee-Carter model”), which we will briefly discuss in this section. The central death rate with age x in year t is denoted by $m_{x,t} = D_{x,t}/E_{x,t}$, where $D_{x,t}$ is the number of deaths at age x and time t and $E_{x,t}$, the exposure-to-risk, is the number of person-years at age x and year t. Lee and Carter (1992) postulate a log bilinear form for the central death rate:

$$\ln(m_{x,t}) = \alpha_x + \beta_x \kappa_t + \epsilon_{x,t} \tag{5.2.1}$$

with time-invariant parameters α_x and β_x, and a homoskedastic error term $\epsilon_{x,t}$ with mean 0 and variance σ^2_ϵ. The parameters in the Lee-Carter model cannot be identified without additional constraints. Lee and Carter (1992) impose that $\sum_t \kappa_t = 0$ and $\sum_x \beta_x = 1$, where κ_t is summed over all time periods and β_x is summed over all available ages in the sample.

Model (5.2.1) can be estimated using singular value decomposition (SVD) as in Lee and Carter (1992). Moreover, to match the estimated death rates with the observed number of deaths in a given year, $D(t) = \sum_x D_{x,t}$, Lee and Carter propose to adjust κ_t after the first step estimation such that

$$D(t) = \sum_x \left[E_{x,t} \exp(\hat{\alpha}_x + \hat{\beta}_x \kappa_t) \right] \tag{5.2.2}$$

where $\hat{\alpha}_x$ and $\hat{\beta}_x$ are estimated parameters from SVD.

The parameter κ_t, often labeled as mortality index, or mortality reduction factor, is a one-dimensional time-dependent latent process that quantifies the variation in the level of mortality over time. The parameters α_x, by construction, represent the average log mortality at given ages, while the parameters β_x capture the sensitivity of the log central death rate at age x to variations in κ_t. Finally, the error terms $\epsilon_{x,t}$ represent the age and time specific variations, not captured by the systematic part.

Mortality prediction is based on the estimated parameters and projection of κ_t. In most studies, the latent variable κ_t is modeled as an ARIMA(p, d, q) process with best fitting form (p, d, q)=(0,1,0), which is a random walk with drift (Lee & Carter, 1992, Lee & Miller, 2001, and Hanewald, 2011), i.e.,

$$\kappa_t = \theta + \kappa_{t-1} + \delta_t \tag{5.2.3}$$

where θ is a drift term and δ_t is a white noise error term.

Many modifications of the original Lee-Carter model have been proposed, see, for example, Lee and Miller (2001), Booth et al. (2002), Cairns et al. (2006), Currie et al. (2004), Plat (2009), and O'Hare and Li (2012), to name a few. A recent review (including many references) is provided by Booth and Tickle (2008).

Despite of the popularity of these stochastic models with latent variables, they also have common limitations. Although the stochastic models are able to identify some historical trends in mortality rates, they are not aiming at explaining what underlies the historical trends nor whether these trends will continue in the future. A more ambitious model might take into account the impact of some exogenous factors (such as biomedical, environmental, or socio-economic factors) on mortality rates. Although it is not easy to identify all relevant variables and to comprehend their mechanisms, it is instructive to start with a few. In the following section, we discuss the relationship between trends in mortality rates and in one of the potential factors, namely economic growth. By choosing GDP as the proxy for economic growth, our approach can be associated with both the extrapolation and the explanation methods. The next section elaborates the reasons.

5.2.2 Economic growth and mortality rates

The relationship between economic growth and health and mortality has been studied for several decades. It is generally accepted that the two variables are closely linked, with causation often going in both directions. In this paper we use GDP to forecast mortality. However, there is also an extensive literature discussing an alternative pathway - the impacts of health on economic outcomes, at both the micro- and the macro- levels. The debate is still ongoing. For example, Bloom et al. (2004) find that good health has a positive and sizeable effect on aggregate output. Bloom et al. (2004) also provide an overview of works that include health as a determinant of economic growth and the magnitude of the effect. Besides, both De la Croix and Licandro (1999) and Bhargava et al. (2001) claim that the effect of life expectancy on growth is positive in low-income countries. On the other hand, Acemoglu and Johnson (2007) find no evidence that exogenous increase in life expectancy resulted in a significant increase in per capita economic growth. While we acknowledge the controversy in the literature, our analysis is based on the hypothesis that in the long run, the trend in economic growth and the one in longevity growth should not diverge from each other to a large extent.

After emphasizing that studying the direction of causality is beyond the scope of this paper, in the following we continue to review the literature on the relationship between economic growth and health. Using cross-country and time series data on health and income per capita, Pritchett and Summers (1996) found a significant positive effect of income on health in the long run. Using individual level data from several surveys, Ettner (1996) documented that increases in income significantly improve mental and physical health, based on both ordinary and IV estimates. Brenner (2005) suggests that economic growth not only reduces poverty through an increase of real income, but also stimulates the investments in new medicines, surgery and prosthetics, and hospital services, which may dramatically increase life expectancy. Applying time series analysis to US data, Brenner (2005) also shows that over the medium- to long-term GDP is strongly negatively related to mortality. Birchenall (2007) argues that improvements in economic conditions are an important force behind mortality decline. The author uses income per capita to measure the economic condition, which is similar to the real GDP per capita in our paper. The effects of wealth on health are not constrained to developing countries. Recently, Swift (2011) applied cointegration analysis to investigate the relationship between health and GDP for 13 OECD countries over the last two centuries, and found that GDP per capita and total GDP have a significant impact on life expectancy for most countries. Nandi et al. (2012) found that monthly rates of death by suicide in New York City are negatively associated with levels of economic activity in New York State.

However, there is only a very limited number of papers studying the role of macroeconomic variables and other observable factors in the context of stochastic mortality models such as the Lee and Carter (1992) model. Recently, using data for six OECD countries over the period 1950 to 2006, Hanewald (2011) studies the impact of macroeconomic fluctuations on mortality dynamics in the Lee-Carter mortality forecasting model, finding that the mortality index κ_t in this model and GDP levels are significantly correlated for the considered time periods and countries.

This paper follows the idea that the latent factors in mortality might be related to some macroeconomic variables. However, instead of building a structural model to study causality, we first begin with a reduced-form approach to study the relationship between the latent factor and the observable factor. By doing so, we aim to provide an alternative perspective on understanding the existing stochastic models and pave the way for future developments of models including explanatory elements. Among a number of potential factors, we focus on the role of economic growth where real GDP per capita is applied as proxy. In the long run, the trend in economic growth, as measured by real GDP per capita, is very likely to be associated with the trend in mortality reduction, which is the main component captured by many of the stochastic mortality models. The use of real GDP as a measure of economic growth is widely documented. Besides, GDP data has a number of merits in a forecasting model. Firstly, GDP is relatively objective and easy to access, making the model more transparent. Secondly, the dynamics of the GDP process has been widely studied in the literature. Moreover, the trend in GDP may capture the trend in the overall economy.

5.3 Mortality and GDP

5.3.1 Data and mortality fitting by the Lee-Carter model

Our analysis in this paper is based on six industrialized countries, namely the United States, the United Kingdom, the Netherlands, Canada, Australia, and Japan, whose mortality dynamics are often investigated in the literature and whose pension systems are exposed to increasing longevity risk. Annual death rates from 1950 to 2007 are obtained from the Human Mortality Database.[2] The time period we select covers the recent mortality trends after World War Two. As mortality data at very old ages are not very reliable, we set the maximum age in our sample to 99, thus the total range of age investigated is $0-99$.[3] The time series of real GDP per capita for each country of the corresponding period is obtained from the Maddison Data on the World Economy.[4] Due to the exponential growth patterns, we take the natural logarithm of the real GDP series. Our dataset is similar to the one in Hanewald (2011). However, we choose real GDP per capita instead of total GDP since the former seems to be a more appropriate measure of economic well-being, as the former is more closely related to individuals' purchasing power.

The Lee-Carter model is estimated under the settings in Lee and Carter (1992) for each country and gender combination. Males and females are treated separately as they show different mortality patterns. In line with the previous literature, the mortality index, κ_t, shows a decreasing trend in each case and can explain a large amount of variance in historical mortality rates. We plot the estimated κ_t in Fig. 5.1. The proportion of the variance explained by the Lee-Carter model (R^2) is given in Table 5.1. There are some differences in terms of model fitting across countries. The mortality rates of Japan are fitted best, with more than 96% of the variance being explained for both genders, followed by the United States, while the Netherlands comes in last (85%). This might not be surprising, given that the Netherlands has the smallest population size.

Compared to the other five countries, the mortality index (κ_t) of Japan also shows a deeper decline for each gender. On the whole, the mortality index shows a decreasing trend in each case and explains a large amount of variance in historical

[2] http://www.mortality.org/

[3] In this regard the probability of survival beyond 99 will be set equal to zero. However, in this paper we focus on life expectancy at early ages so that the survival probability beyond 99 has little impact.

[4] http://www.ggdc.net/MADDISON/oriindex.htm

mortality rates, which is in line with the previous literature.

Table 5.1: Proportion of variance explained by Lee-Carter model (R^2)

	United States	Canada	United Kingdom
Female	0.9561	0.9258	0.9176
Male	0.9379	0.9256	0.9209
	Netherlands	Australia	Japan
Female	0.8569	0.9079	0.9627
Male	0.8562	0.9067	0.9651

5.3.2 Long run relationship between mortality and GDP

In this section we examine the time-series properties of the latent factor in the Lee-Carter model and the GDP process, with a focus on the long run relationship between the two series.

We start with testing the stationarity of the mortality index (κ_t) and the real GDP per capita in logarithm (g_t) in each country. First, we apply the Phillips-Perron test (Perron, 1988) in the most general setting, with the inclusion of a constant and a linear time trend.[5] The results of the tests are in panel A of Table 5.2. For female κ_t, we can only reject the null of nonstationarity for UK and Japan at the 1% significance level. For male κ_t, the null of nonstationarity is rejected for Japan at the 5% significance level. For GDP, we can only reject the null of nonstationarity for US and UK, at the 10% and at 5% significance level, respectively. For those stationary series, we find that they are trend stationary. However, in a finite sample it is very difficult to distinguish between difference-stationary and trend-stationary behavior, and the assumption of difference-stationarity might be more prudent. In general, the results indicate that most of the series are not stationary. As a supplementary analysis, we perform the KPSS test developed by Kwiatkowski et al. (1992) with

[5]Hanewald (2011) performs similar unit root tests. The main differences are, first, that she uses the Brouhns et al. (2002) variant of the Lee-Carter model while we maintain the original settings. Second, she uses real GDP in levels while our analysis is based on real GDP per capita in logarithm. However, the main results are similar.

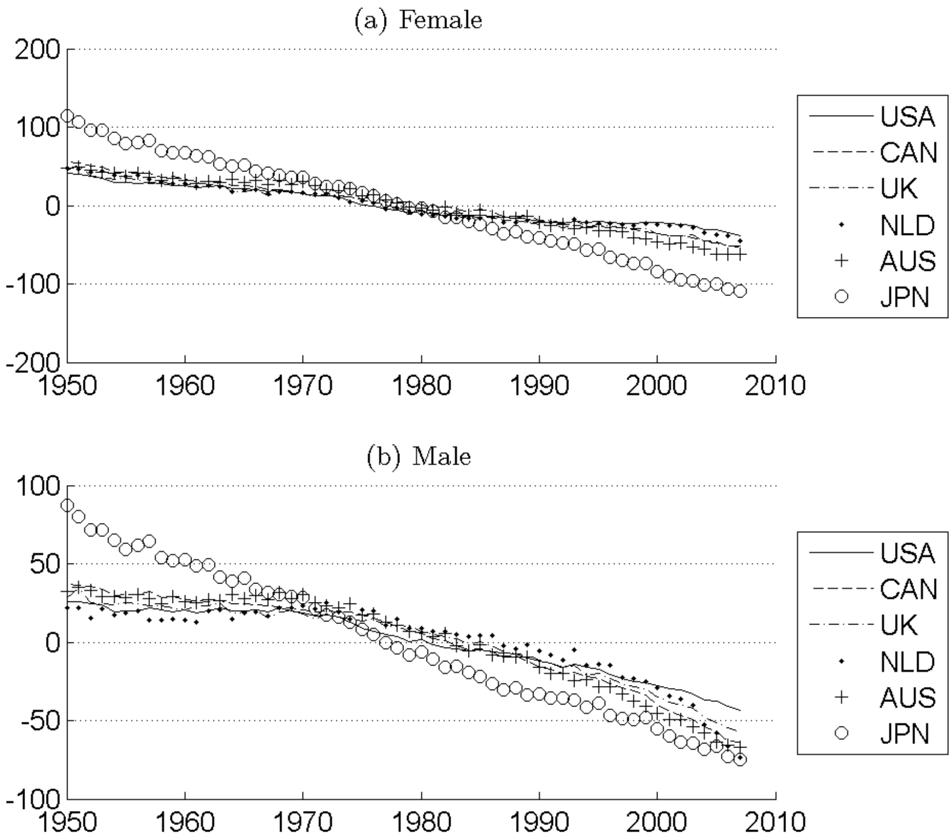


Figure 5.1: Mortality index (κ_t) of each country (1950-2007)

Table 5.2: Results of unit root tests: test statistics

	United States	Canada	United Kingdom	Netherlands	Australia	Japan
Panel A: Levels of the Time Series (Phillips-Perron Test)						
$\kappa_{t,female}$	-7.06	-11.10	-28.67^{***}	-7.98	-8.05	-32.74^{***}
$\kappa_{t,male}$	-1.69	0.96	0.40	4.07	-1.23	-22.13^{**}
g_t	-18.96^{*}	-4.84	-22.35^{**}	-8.92	-9.18	-0.35
Panel B: Levels of the Time Series (KPSS Test)						
$\kappa_{t,female}$	0.40^{***}	0.38^{***}	0.43^{***}	0.45^{***}	0.53^{***}	0.23^{***}
$\kappa_{t,male}$	0.59^{***}	0.68^{***}	0.71^{***}	0.64^{***}	0.70^{***}	0.39^{***}
g_t	0.23^{***}	0.54^{***}	0.13^{*}	0.56^{***}	0.31^{***}	0.72^{***}
Panel C: First Difference (Phillips-Perron Test)						
$\kappa_{t,female}$	-66.95^{***}	-74.49^{***}	-78.76^{***}	-70.48^{***}	-80.20^{***}	-65.14^{***}
$\kappa_{t,male}$	-66.68^{***}	-69.98^{***}	-76.40^{***}	-74.50^{***}	-78.04^{***}	-63.10^{***}
g_t	-50.28^{***}	-42.00^{***}	-35.55^{***}	-43.18^{***}	-40.42^{***}	-30.64^{***}

Note: ${}^{*}p < 0.10$, ${}^{**}p < 0.05$, and ${}^{***}p < 0.01$.

the null hypothesis that the time series is trend-stationary, the results of which are shown in Panel B of Table 5.2. The null of stationarity is rejected at the 1% significance level without exception. Therefore, we proceed under the assumption of the presence of a unit root in the time series. We perform a similar analysis on the first differences of the series. Panel C of Table 5.2 gives the test statistics of the Phillips-Perron test. The null of nonstationarity is rejected at the 1% significance level for each series. In brief, the above analysis indicates that the time series are $I(1)$ processes.

The nonstationary series κ_t and g_t can be analyzed in first differences. However, as also argued in Hanewald (2011), such a transformation might miss the long term properties of the data. A common strategy to study the long-run relationship among time series data is a cointegration analysis. Two or more nonstationary series are said to be cointegrated if they are integrated of the same order and a linear combination of them is stationary. The linear combination can be interpreted as a long-run equilibrium among the series.

Hanewald (2011) applied the Engle-Granger procedure (Engle & Granger, 1987) to test the cointegration between the mortality index, κ_t, and real GDP level in six OECD countries and different age groups. Her findings are, however, mixed. Approximately one quarter of her results indicate the existence of cointegration relationships, while the remaining results do not. As a complementary analysis, we directly study the long run relationship between log central death rates and log real GDP per capita at each age by the Engle-Granger procedure. Formally, we are testing the stationarity of the estimated residuals, $\hat{\epsilon}^g_{t,x}$, from the regression[6]

$$\ln(m_{x,t}) = \gamma_{0,x} + \gamma_{1,x} g_t + \epsilon^g_{x,t} \tag{5.3.1}$$

for each age x, $x = 0, 1, \ldots, 99$. As a comparison, we also study the long-run implications between the log central death rates and the mortality index κ_t. More specifically, we apply the Engle-Granger procedure to the model

$$\ln(m_{x,t}) = \beta_{0,x} + \beta_{1,x} \kappa_t + \epsilon^\kappa_{x,t} \tag{5.3.2}$$

for each age x, $x = 0, 1, \ldots, 99$.

Detailed results are presented in the online appendix. In general, the Engle-Granger test indicates mixed results. The mortality rates are found to be cointegrated with real GDP (g_t) or the mortality index (κ_t) only at certain ages. Besides, in terms of presenting cointegration relationships under the Engle-Granger procedure, neither κ_t nor g_t dominates the other.

It is often argued that in finite samples the power of the cointegration analysis is often too small to discover a potential cointegration relationship. Besides, the Engle-Granger procedure requires the specification of dependent and independent variables in the test while a vector error correction model (VECM) does not have this concern. As a complement, we build a VECM for the mortality index and the

[6]Based on results from the augmented Dickey-Fuller test, most of $\ln(m_{x,t})$ are I(1) processes.

Table 5.3: Johansen cointegration test statistic

	Females					
	United States	Canada	United Kingdom	Netherlands	Australia	Japan
$r \leq 1$	5.12	6.54	8.94	4.53	3.58	5.52
r=0	30.54	44.10	25.95	30.77	50.92	36.15
	Males					
	United States	Canada	United Kingdom	Netherlands	Australia	Japan
$r \leq 1$	4.50	5.91	5.40	14.30	6.78	4.44
r=0	35.23	43.01	32.21	46.50	58.24	29.49

Note: Critical values for the null of $r = 0$ are: 13.73 for $p < 0.10$, 15.17 for $p < 0.05$, and 20.20 for $p < 0.01$. Critical values for the null of $r \leq 1$ are: 7.52 for $p < 0.10$, 9.24 for $p < 0.05$, and 12.97 for $p < 0.01$.

macroeconomic indicator and perform the Johansen (1988) cointegration tests. [7]

The test results, shown in Table 5.3, support the existence of cointegration relationships between the mortality index and the macroeconomic indicator much stronger than the results in Hanewald (2011). The null of no cointegration ($r = 0$) is rejected in all cases at a significance level of 1%, while the null of one cointegration vector ($r = 1$) cannot be rejected at a significance level of 5% in all cases except for Dutch males. Above all, the analysis in this section indicates possible long run relationships between the macroeconomic indicator, real GDP per capita, and the mortality rates, which motivates us to compare their trends in more details in the following sections.

5.4 Trend comparison: Mortality and GDP

In this section, we begin with comparing the in-sample goodness-of-fit between the Lee-Carter model and a model with GDP per capita as the regressor. Secondly, we forecast mortality rates by extrapolating GDP per capita and compare the results to the ones from the Lee-Carter model. By doing this, we can compare the trend in mortality rates and the trend in economic growth from a new perspective.

[7] We multiplied the test statistics by a factor $(T - pk)/T$, where p denotes the number of lags in the VAR model and k denotes the number of variable. This is to correct small sample bias, as suggested in Ahn and Reinsel (1990).

First, we compare their performance on fitting historical data. The goodness of fit between the model based on the Lee-Carter mortality index and the model based on the real GDP per capita series are very similar. The goodness of fit is measured by the R^2-s from model (5.3.1) and model (5.3.2) based on ordinary least squares. The results are available in the online appendix. In general, the mortality index and the macroeconomic indicator have comparable performance in fitting historical mortality data. We further study their implications on the trend and variance of future mortality rates. We fit historical mortality rates by the mortality index (κ_t) or real GDP per capital in logarithm (g_t), according to equation (5.3.1) and (5.3.2), see the previous section. The prediction of future mortality rates is based on the forecasts of κ_t or g_t, where we rely on $ARIMA$ models. In most cases, the series is modeled most appropriately by a random walk with drift model. Following common practice, to correct for a jump-off bias in mortality fitting, we calculate the predicted changes of future mortality rates and base our projections on the actual rates in the final year of the estimated sample. This adjustment is performed for both the Lee-Carter model and the model based on GDP.

Using historical data from 1950 to 2007, we forecast future mortality rates based on the procedures mentioned above. As life expectancy is an often used summary of mortality, we project period life expectancies at birth 30 years ahead. The use of period life expectancies, instead of cohort life expectancies, is common in the literature and in practice.[8] To account for the forecast uncertainty, we calculated 95% confidence bounds for the $ARIMA$ models for κ_t and g_t. To focus on the comparison between κ_t and g_t, uncertainties in other parts of the Lee-Carter model, such as $\epsilon_{x,t}$ in equation (5.2.1), are not taken into account.

Figure 5.2 shows the results for females. Results for males are shown in the online appendix. The forecasted mean values and confidence intervals by the Lee-Carter model and the model with GDP almost coincide in three countries (the United

[8]Furthermore, cohort life tables are based on the projections over very long time period. Thus, the forecast of cohort life tables is more sensitive to the underlying model and estimation methods.

Stated, Canada, and the Netherlands). For the other countries, apart from the fact that the forecasts based on the Lee-Carter model have wider intervals, the mean predictions are still similar.[9] The life expectancy at age zero for females is expected to increase to around 85 in most countries. The expected increase in life expectancy in Japan is more dramatic, with a figure about 5 years higher than the ones in other counties. The result implies that if the target is forecasting long-term mortality, we may replace the latent factor in the Lee-Carter model with an observable one, and still achieve comparable results. Moreover, the forecast of GDP can be associated with future economic scenarios. For instance, the upper bound of the forecasted mortality rates in our model coincides with a lower economic growth prediction while the lower bound is related to a higher economic growth prediction.

5.5 A Generalized Model

In this section we study a stochastic mortality model that includes both latent and observable factors, where in our case GDP is the observable factor. This model can be regarded as a generalized version of the original Lee-Carter method. We will begin with the model setup and estimation methods, followed by the estimation results, and then we study the implied mortality projections.

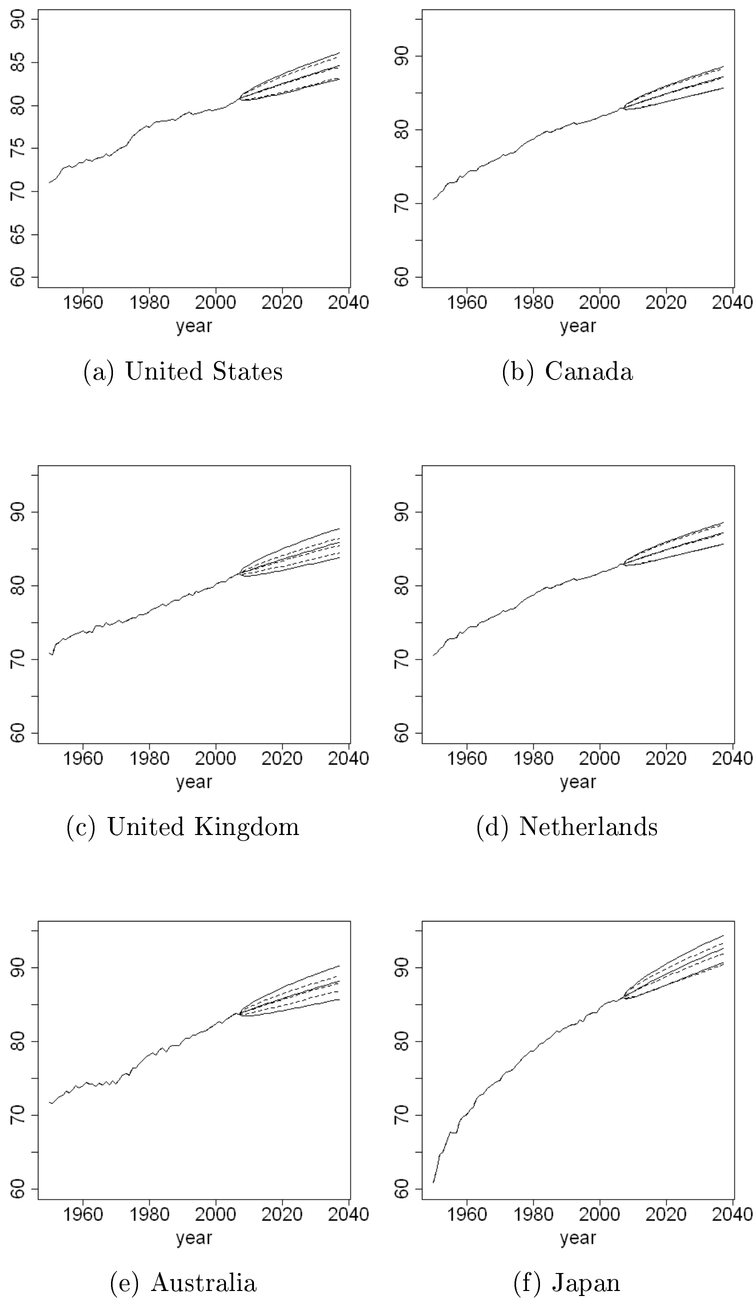
5.5.1 Model setup and estimation method

We postulate that the logarithm of the central mortality rate, $\ln(m_{x,t})$, has a linear form

$$\ln(m_{x,t}) = \alpha_x + \beta_x \kappa_t + \gamma_x g_t + \epsilon_{x,t}, \tag{5.5.1}$$

with time-invariant parameters α_x, β_x, and γ_x, and a time varying latent variable κ_t. $\epsilon_{x,t}$ is a error term that is uncorrelated with κ_t and g_t. α_x, β_x and κ_t have similar

[9] In order to better fit the in-sample mortality rates at different ages, the Lee-Carter κ_t is more volatile than the GDP series, possibly yielding better out-of-sample point forecasts, but also at the expense of a larger prediction interval.



(a) United States (b) Canada

(c) United Kingdom (d) Netherlands

(e) Australia (f) Japan

Figure 5.2: Historical and forecasted life expectancy at birth (e_0),with 95% intervals included (Females). Solid lines represent the results from the Lee-Carter model (5.2.1) and dashed lines from model (5.3.1)

interpretations as in the original Lee-Carter model. The newly included parameter, γ_x, measures the sensitivity of mortality rates at age x to the observable factor (real GDP per capita in logarithm in this paper). For a better interpretation of α_x, the observable factor g_t in the model is demeaned before estimation, implying that α_x will be the average log central death rate across time, just like in the original Lee-Carter model. The model we propose includes as special cases two groups of models. If we let $\gamma_x = 0$, then we have the standard Lee-Carter model. If, otherwise, we assume that $\beta_x = 0$, we have model (5.3.1) in the previous section.

Let $\mu_{x,t}$ denote the systematic part of $\ln(m_{x,t})$ and suppose that a set of parameters

$$\theta = (\alpha_1, \ldots, \alpha_X, \beta_1, \ldots, \beta_X, \kappa_1, \ldots, \kappa_T, \gamma_1, \ldots, \gamma_X) \tag{5.5.2}$$

is given. The parameters are not identified without additional constraints as for any scalar c, any scalar e, and any scalar $d \neq 0$ it holds that

$$\begin{aligned}
\mu_{x,t} &= \alpha_x + \beta_x \kappa_t + \gamma_x g_t \\
&= \alpha_x + \beta_x(\kappa_t - e g_t) + (\gamma_x + e\beta_x) g_t \\
&= (\alpha_x - \beta_x c) + \frac{\beta_x}{d}\{d(\kappa_t - e g_t + c)\} + (\gamma_x + e\beta_x) g_t \\
&= \tilde{\alpha}_x + \tilde{\beta}_x \tilde{\kappa}_t + \tilde{\gamma}_x g_t
\end{aligned} \tag{5.5.3}$$

where

$$\tilde{\alpha}_x = \alpha_x - \beta_x c \tag{5.5.4}$$

$$\tilde{\beta}_x = \beta_x / d \tag{5.5.5}$$

$$\tilde{\kappa}_t = d(\kappa_t - e g_t + c) \tag{5.5.6}$$

$$\tilde{\gamma}_x = \gamma_x + e\beta_x \tag{5.5.7}$$

We propose the following four normalization constraints.

$$\sum_t \kappa_t = 0 \tag{5.5.8}$$

$$\sum_x \beta_x = 1 \tag{5.5.9}$$

$$cov(\kappa_t, g_t) = 0 \tag{5.5.10}$$

$$\kappa = (\kappa_1, \ldots, \kappa_T) \neq 0 \tag{5.5.11}$$

where the covariance in (5.5.10) will be calculated in-sample.[10] Following Nielsen and Nielsen (2010), the next theorem shows that our constraints identify the parameters uniquely. The proof is given in the appendix.

Theorem 1. *Let* $\mu = (\mu_{x,t}, x = 1, \ldots, X, t = 1, \ldots, T)$*, where* $\mu = \mu(\theta)$ *satisfies* $\mu_{x,t} = \alpha_x + \beta_x \kappa_t + \gamma_x g_t$ *for some* θ *as given by* (5.5.2) . *Then the parametrization* θ^o *where* $\sum_{x=1}^{X} \beta_x^o = 1$, $\sum_{t=1}^{T} \kappa_t^o = 0$, $cov(\kappa_t^o, g_t) = 0$ *in sample, and* $\kappa^o \neq 0$*, satisfies*

(i) θ^o *is a function of* θ*.*

(ii) μ *is a function of* θ *through* θ^o*.*

(iii) The parametrization of μ *by* θ^o *is exactly identified. That is, if* $\theta^1 \neq \theta^2$ *are two parameters satisfying the normalizing constraints, then* $\mu(\theta^1) \neq \mu(\theta^2)$*.*

Model (5.5.1) is fitted to age-specific observed central mortality rates and time series of observable factors using the least squares approach. Specifically, the parameters are such that they minimize a quadratic loss function. A standard iteration optimization method is used to solve for the parameters. See, for example, Wilmoth (1993) for details.

[10]Compared to the Lee-Carter model, we add constraint (5.5.11), namely, $\kappa = (\kappa_1, \ldots, \kappa_T) \neq 0$. Constraint (5.5.11) is needed to identify β_x. This constraint is also required in the Lee-Carter model to identify β_x. If (5.5.11) is not satisfied, i.e. $\kappa = 0$, then our model reduces to model (5.3.1).

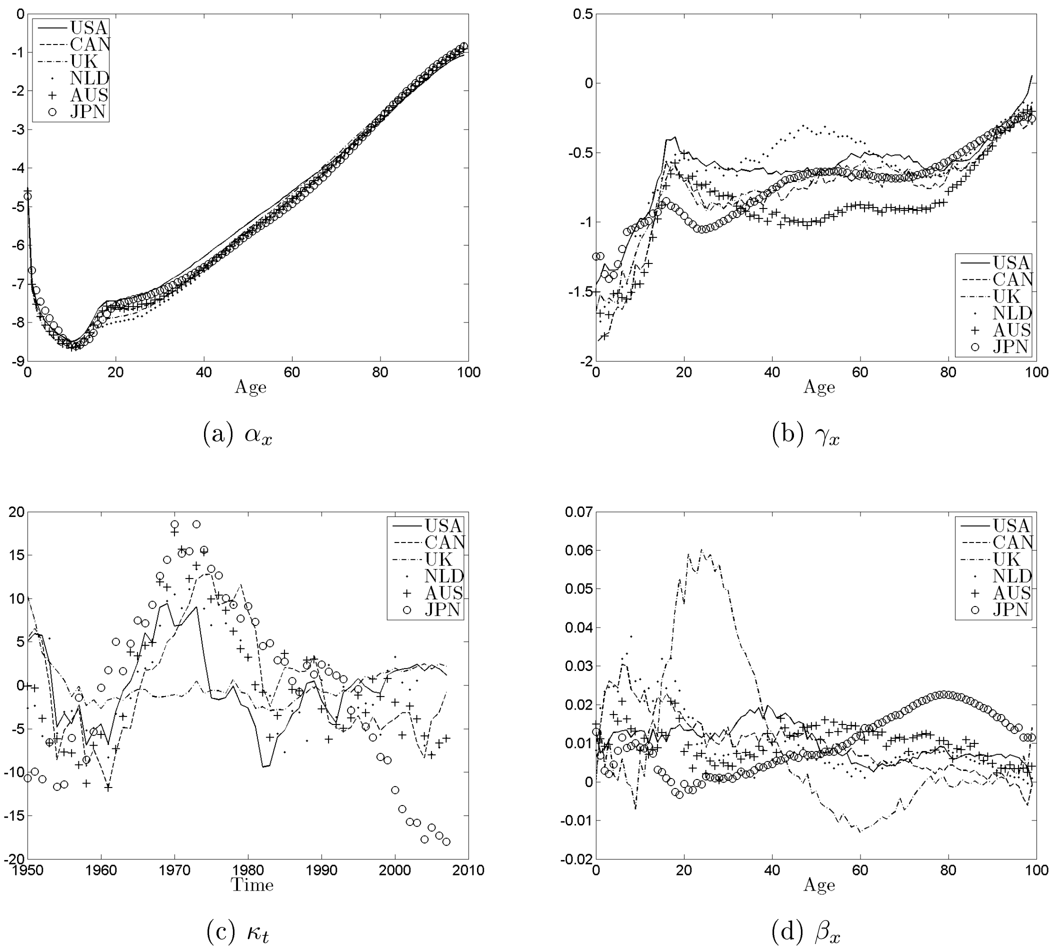
5.5.2 Estimation results

We use the same dataset of the six OECD countries as in the previous section. The results for females are shown in Fig. 5.3. Results for males are presented in the online appendix. The patterns of average mortality (over time) across ages, measured by α_x, are quite similar in our sample countries. The values of β_x vary more between countries. For females, the values of β_x in the United Kingdom are relatively high at younger ages and low at old ages, which is contrary to the pattern in Japan. The parameters γ_x capture the sensitive of mortality rates towards real GDP at different ages, which are relatively similar across countries. Mortality rates at very young ages are most closely related with economic growth. The γ_x-s are negative in general, due to the decreasing trend in mortality rates and the increasing trend in GDP. One striking difference between our method and the Lee-Carter model is the role of the latent factor. There is no clear time trend in κ_t anymore as the time trend is now mostly captured by g_t. Besides, κ_t in our model, with average slope as function of time being around -0.8, is much flatter than the corresponding κ_t in the Lee-Carter model, whose slope is close to -4. Moreover, κ_t-s have large swings in our sample period, indicating that there might be nonlinear time effects captured by κ_t-s. In general, β_x-s are similar across ages and countries, except for females in UK.

We use the Bayesian information criterion (BIC) to compare the goodness-of-fit between our model and the Lee-Carter model. The BIC is a popular criterion that takes into account the balance between parsimony and goodness-of-fit of a model. In our case, the BIC is defined as

$$BIC = N \log(\hat{\sigma}_\epsilon^2) + \nu \log N, \tag{5.5.12}$$

where $\hat{\sigma}_\epsilon^2$ is estimated variance of the error term, ν is the difference between the



(a) α_x (b) γ_x

(c) κ_t (d) β_x

Figure 5.3: Parameters of model (5.5.1) (Females)

Table 5.4: Fit of Model (5.5.1) and Lee-Carter model: Bayesian information criterion (BIC)

	Female		Male	
	Model (5.5.1)	Lee-Carter	Model (5.5.1)	Lee-Carter
United States	-32056	-30526	-31555	-29597
Canada	-25017	-24292	-26400	-24172
United Kingdom	-26182	-25297	-28025	-25357
Netherlands	-22211	-21816	-24355	-19068
Australia	-22573	-22743	-23848	-22833
Japan	-26051	-16931	-27033	-23553

number of parameters and the number of constraints,[11] and N is the number of observations. Under the assumption that the errors are independent and identically distributed according to a normal distribution, $\log(\hat{\sigma}_\epsilon^2)$ is proportional to the maximum log likelihood.

Values of BIC are shown in Table 5.4. A smaller (more negative) value indicates a better model fit. Our model outperforms the Lee-Carter model in every case of country and gender combination, except for the Australian females. The improvement of goodness-of-fit is mostly apparent in Japanese female data, as reflected in the large difference between the BIC values.

As mentioned before, the standard Lee-Carter model is a restricted version of our generalized model, when $\gamma_x = 0$ for all x. To examine whether the estimation based on our model provides more information than the standard Lee-Carter model, we test the null hypothesis that $\gamma_x = 0$ for each x based on bootstrapping the residuals of our model. To be specific, in each bootstrap simulation, we draw randomly with replacement from the residuals in (5.5.1) to construct a new sample and re-estimate the parameters. The results indicate that the estimated γ_x-s are significantly different from zero at all conventional significance levels.

[11] According to equations (5.5.8), (5.5.9), (5.5.10), and (5.5.11), we have four constraints. However, constraint (5.5.11) is only examined ex post and is not included in the estimation, similar to the Lee-Carter model, so the effective number of constraints is three.

Table 5.5: Proportion of variance explained by Model (5.5.1)

	Female			Male		
	κ_t	g_t	Total	κ_t	g_t	Total
United States	0.0383	0.9244	0.9627	0.0797	0.8775	0.9572
Canada	0.0527	0.8816	0.9343	0.1161	0.8291	0.9452
United Kingdom	0.0314	0.8969	0.9283	0.0622	0.8810	0.9431
Netherlands	0.0557	0.8119	0.8676	0.1580	0.7415	0.8996
Australia	0.0441	0.8689	0.9131	0.0920	0.8317	0.9237
Japan	0.0415	0.9410	0.9825	0.0475	0.9292	0.9767

To examine the relative contribution of different factors to the model fit, we present in Table 5.5 the proportion of the variance explained by the latent variable (κ_t) and GDP (g_t), respectively, together with the total fraction of variance captured by model (5.5.1). In all cases, GDP accounts for the major variance explained by model (5.5.1), while κ_t only explains a marginal amount of the variance, less than 10%, except for males in Canada and Japan. Besides, as a whole, the model we propose can explain a large amount of the variance in the data.

5.5.3 Out-of-Sample test

In this section we compare the out-of-sample forecast accuracy between the Lee-Carter model and (5.5.1). We use 50 years data on death rates (from 1950 to 1999) to fit the two models, and then forecast death rates from 2000 to 2007 accordingly. The forecast of model (5.5.1) is based on the projections of estimated g_t and the latent factors, while the forecast of the Lee-Carter model is based solely on the estimated latent factors. For latent factors in both models, we forecast them by standard AR models, with lags selected based on BIC. For the log real GDP per capita series, we use the random walk with drift model to forecast future values. We do not use vector autoregressive models, because in our model the latent factor is orthogonal to the GDP series by construction.

Table 5.6: Out-of-sample test results: RMSFE for females

Country	USA	CAN	UK	NLD	AUS	JPN
LC	0.0070	0.0066	0.0045	0.0084*	0.0043*	0.0227
LC-GDP	0.0069*	0.0055*	0.0043*	0.0088	0.0044	0.0081*

The forecast results are compared using the Root Mean Square Forecast Error (RMSFE). Specially, denote y_{it} the true death rate at age i and year t, and $\hat{y}_{it}$ the corresponding forecasted death rates. The RMSFE is calculated according to the formula:

$$RMSFE = \sum_t \sum_i (y_{it} - \hat{y}_{it})^2 \tag{5.5.13}$$

Table 5.6 shows the out-of-sample test results for females. LC refers to the Lee-Carter model, and LC-GDP refers to the model based on GDP. For each country the specification with smaller RMSFE is marked with an asterisk. The model with GDP is better in four out of the six cases. In particular, compared the Lee-Carter model, our model reduces the forecasting errors by 17% in Canada and by 64% in Japan. Although the Lee-Carter model is better for the Netherlands and Australia, the two countries also have the smallest population size. Thus, for the two countries, there might be overfitting in our model, due to the presence of additional κ_t, to random fluctuations in the data.

5.5.4 Forecasting using the proposed model

Forecasting future mortalities is a natural application of our model. In this section we briefly illustrate the implications of this model forecast by both genders in each country.

Using historical data from 1950 to 2007, we forecast future mortality rates based on the time series models of g_t and κ_t and estimated parameters for model (5.5.1), then project period life expectancies at birth 30 years ahead. We focus on two sources of uncertainty in forecasted mortality rates, which are the uncertainty in forecasted GDP and in forecasted κ_t. We construct the forecast intervals (2.5% and

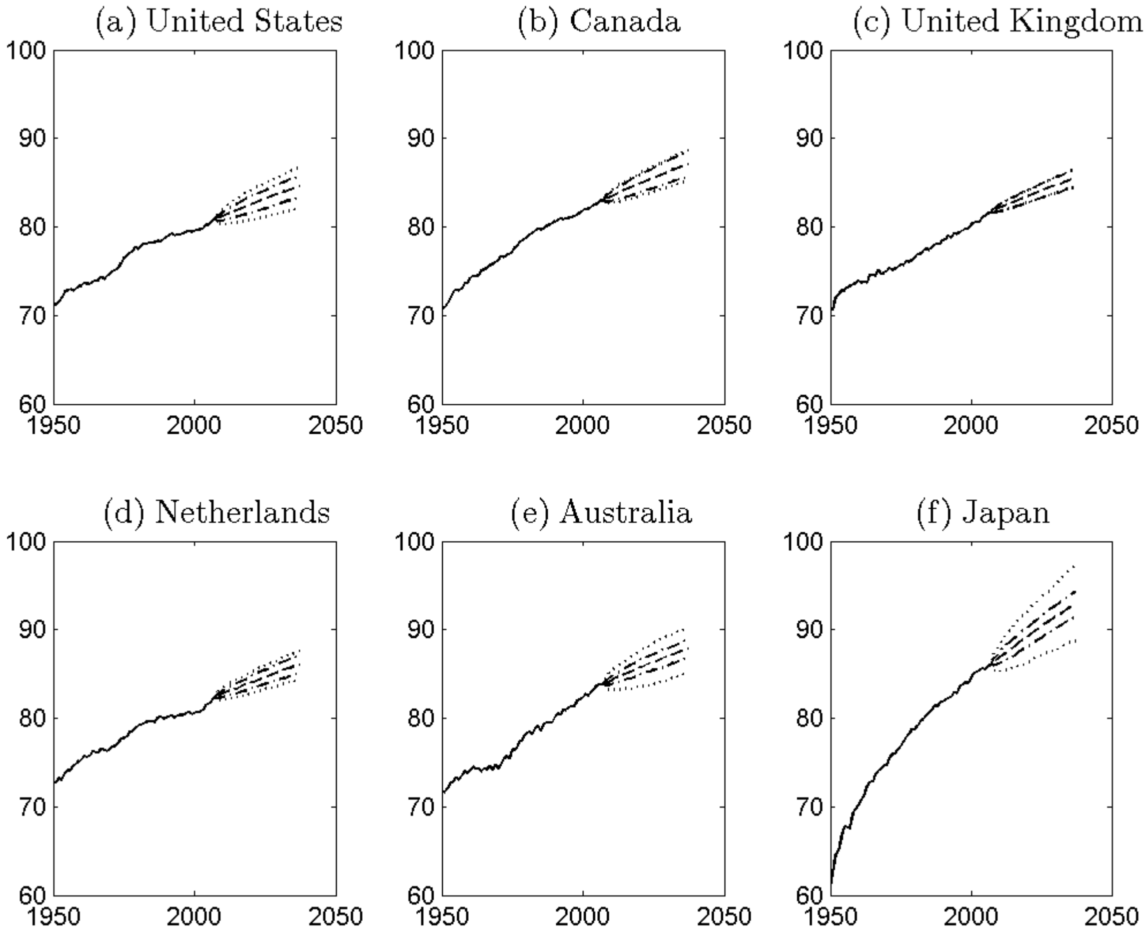


Figure 5.4: Historical and forecasted life expectancy at birth (e_0),with 95% intervals included (Females). Solid lines represent the historical data, dashed lines the forecasted mean values from model (5.5.1), dash-dotted lines the 95% bounds including only the variations in g_t, and dotted lines the 95% bounds including the variations in both g_t and κ_t.

97.5% quantiles) by 1000 simulations. To compare the uncertainty from different sources, we construct two types of intervals. The first intervals are based on the simulation of future g_t only, with the mean values of κ_t being projected. The second interval is based on the simulations of both g_t and κ_t. The results for females are shown in Fig. 5.4 and results for males are presented in the online appendix.

The life expectancies at birth for females are predicted to increase to around 85 in 30 years in five countries except Japan, where the figure is as high as 90. The dash-dotted lines are the intervals based on the uncertainty in future GDP, which can be interpreted as different economic scenarios. The differences between life expectancies of lower and upper confidence intervals are within five years.

The uncertainty brought in by κ_t depends on its volatility. As can be seen in Fig. 5.3 (c), the estimated female κ_t is least volatile in UK, corresponding to the narrowest intervals in our forecasts, represented by dotted lines in Fig. 5.4, while the estimated female κ_t is most volatile in Japan, corresponding to the widest intervals.

5.6 Conclusion

Based on data from 1950 to 2007 of six OECD countries, namely the United States, Canada, the United Kingdom, the Netherlands, Australia, and Japan, this paper performs a comprehensive investigation of the relationship between the trends in mortality dynamics and economic growth. The former trend is represented by the latent mortality index κ_t in the Lee-Carter model while the latter is represented by the real GDP per capita series g_t. We also present an extension of the Lee-Carter model that includes both latent and observable factors.

We have compared the Lee-Carter model with a mortality model based solely on real GDP per capita in terms of both in-sample fitness and future projections. The results are quite similar in both aspects, indicating the similarity between the two trends of interest. Thus, the trend in economic growth might be an observable substitute to the latent variable. Nonetheless, this latent variable still explains a certain level of non-random variations in mortality rates, suggesting that economic growth might not be the only factor that is related to longevity. Based on the long-run relationship between economic growth and mortality decline, we augment the Lee-Carter model with an economic growth indicator and apply the model to mortality rates of six countries. Mortality forecasts in our model are based on projecting both the latent factor and the real GDP series. In this sense, our model integrates two major mortality forecast methods in the literature, namely the extrapolation method and the explanation method. When both the economic growth indicator and the latent variable are included in our generalized mortality model, we have a better goodness-of-fit and the role of latent factor is marginal, implying that the major trend in mortality rates is captured by real GDP data. Our model also can generate more interpretable scenarios about future longevity based on the forecast of future economic growth.

The role of economic growth on mortality dynamics deserves further investigation. Currently, a clear explanation for mortality decline is still lacking. However, the similarity between trends in mortality reduction factors and economic growth might shed light on possible directions towards explaining the trend. Besides, the method in our paper can be extended to include other related factors, both latent variables and observable variables.

Acknowledgments

For comments and discussions, we thank two anonymous referees, the editor, Makov Udi, Qihe Tang, Jochen Mierau, and participants at the 7th Conference in Actuarial Science and Finance in Samos, the 2012 Tilburg University GSS seminar in Tilburg, and the 2012 Netspar Pension Day in Utrecht.

Appendix

5.7 Proof of Theorem 1

Proof. (i) For any θ we can construct θ^o by using (8) and letting $d = \sum_{x=1}^{X} \beta_x$, $c = -\frac{\sum_{t=1}^{T} \kappa_t}{T}$, and $e = \frac{cov(\kappa_t, g_t)}{var(g_t)}$.

(ii) One can transform θ^o into the original θ by $d^o = \frac{1}{d}$, $c^o = -cd$ and $e^0 = -ed$. The parametrization (8) is invariant to c, d, e.

(iii) Consider $\theta^1 \neq \theta^2$.

Step 1 If $\alpha_x^1 \neq \alpha_x^2$ for some x then $\frac{1}{T}\sum_{t=1}^{T} \mu_{x,t}^1 = \alpha_x^1 \neq \alpha_x^2 = \frac{1}{T}\sum_{t=1}^{T} \mu_{x,t}^2$.

Step 2 If $\gamma_x^1 \neq \gamma_x^2$ for some x, then, since $cov(\kappa_t, g_t) = 0$, it holds $cov(g_t, \mu_{x,t}^1) = \gamma_x^1 var(g_t) \neq \gamma_x^2 var(g_t) = cov(g_t, \mu_{x,t}^2)$.

Step 3 If $\alpha_x^1 = \alpha_x^2$ and $\gamma_x^1 = \gamma_x^2$ for all x, but $\kappa_t^1 \neq \kappa_t^2$ for some t, then, since $\sum_{x=1}^{X} \beta_x = 1$, it holds

$$\begin{aligned}\sum_{x=1}^{X} \mu_{x,t}^1 &= \kappa_t^1 - \sum_{x=1}^{X} \alpha_x^1 - \sum_{x=1}^{X} \gamma_x^1 g_t \\ &\neq \kappa_t^2 - \sum_{x=1}^{X} \alpha_x^2 - \sum_{x=1}^{X} \gamma_x^2 g_t = \sum_{x=1}^{X} \mu_{x,t}^2.\end{aligned}$$

Step 4 If $\alpha_x^1 = \alpha_x^2$ and $\gamma_x^1 = \gamma_x^2$ for all x, $\kappa_t^1 = \kappa_t^2$ for all t, and $\kappa \neq 0$, but $\beta_x^1 \neq \beta_x^2$ form some x, then we can find $\kappa_{t_1}^2 = \kappa_{t_1}^1 \neq \kappa_{t_2}^1 = \kappa_{t_2}^2$, such that $\mu_{x,t_2}^1 - \mu_{x,t_1}^1 = \beta_x^1(\kappa_{t_2}^1 - \kappa_{t_1}^1) \neq \beta_x^2(\kappa_{t_2}^2 - \kappa_{t_1}^2) = \mu_{x,t_2}^2 - \mu_{x,t_1}^2$.

□

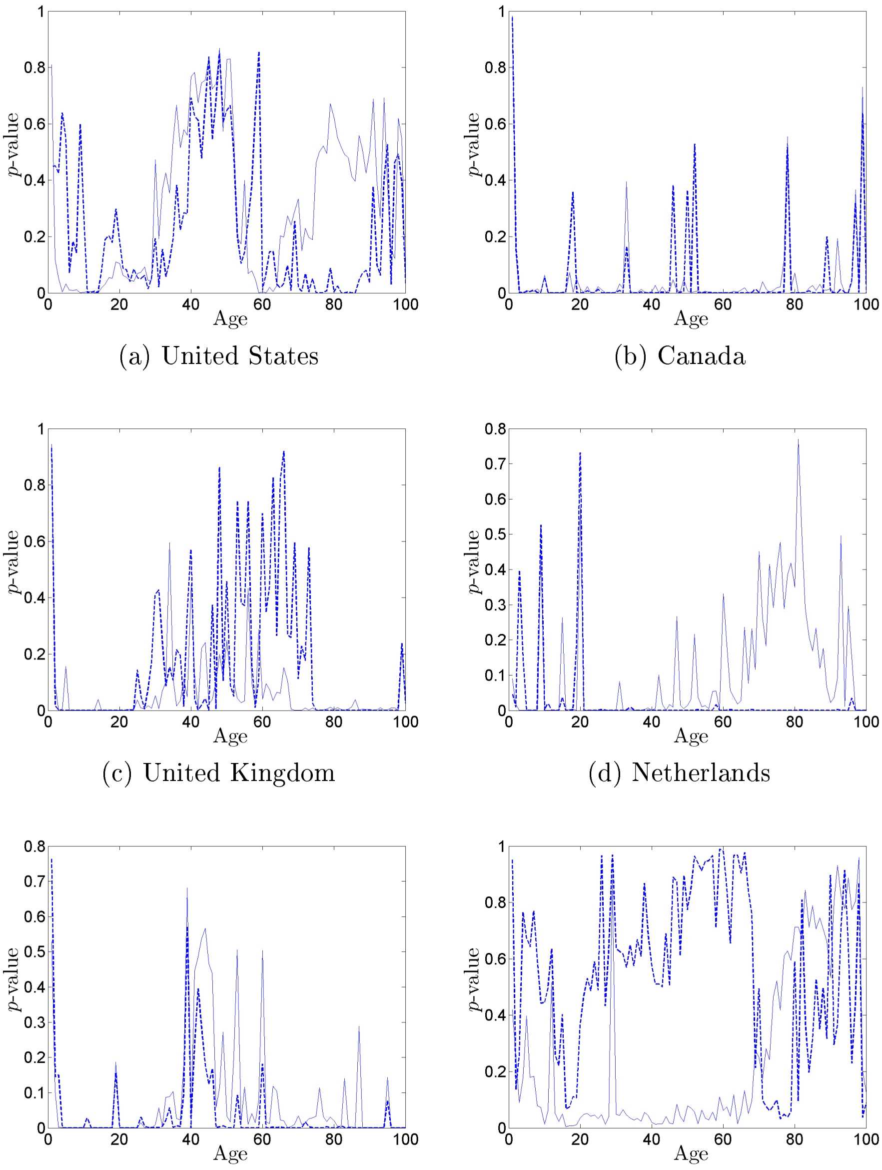
5.8 Additional results on the similarity between κ_t and g_t

This section provides detailed results with regard to the Engle-Granger cointegration analysis in section 3 and the comparison of goodness of fit in section 4.

In the Engle-Granger cointegration analysis, we test the stationarity of the estimated residuals from equation (4) and equation (5) at each age for females and males separately. To test the stationarity of the residuals, the standard critical values for unit root tests are not appropriate, as the regression will make the residuals as stationary as possible. We use the more negative critical values provided by MacKinnon (1996). The optimal lag length for the ADF test of the residuals is determined based on the Bayesian (Schwarz) information criterion (BIC) with a maximum length of 10. As a comparison, we also study the long-run implications between the log central death rates and the mortality index κ_t.

To facilitate the reading of the results, the p-value of the cointegration tests at each age are plotted in Fig. 5.5 for females and 5.6 for males. There are several implications in the graphs that are worth noticing. First, in terms of presenting cointegration relationships under the Engle-Granger procedure, neither κ_t nor g_t dominates the other. Second, the results vary across countries and ages for both κ_t and g_t. Particularly, the mortality rates at middle ages are not cointegrated with real GDP in most cases. Third, there are a certain amount of cases indicating that the real GDP per capita series and mortality rates are cointegrated, especially for females in Canada.

Next, we compare the goodness of fit between the model based on the Lee-Carter mortality index and the model based on the real GDP per capita series. The goodness of fit is measured by the R^2-s from the regression (4) and (5) based on ordinary least squares. The results are plotted in Fig. 5.7 and Fig. 5.8 for each age. The two series seem to be closest for the groups of Canada females, US males,

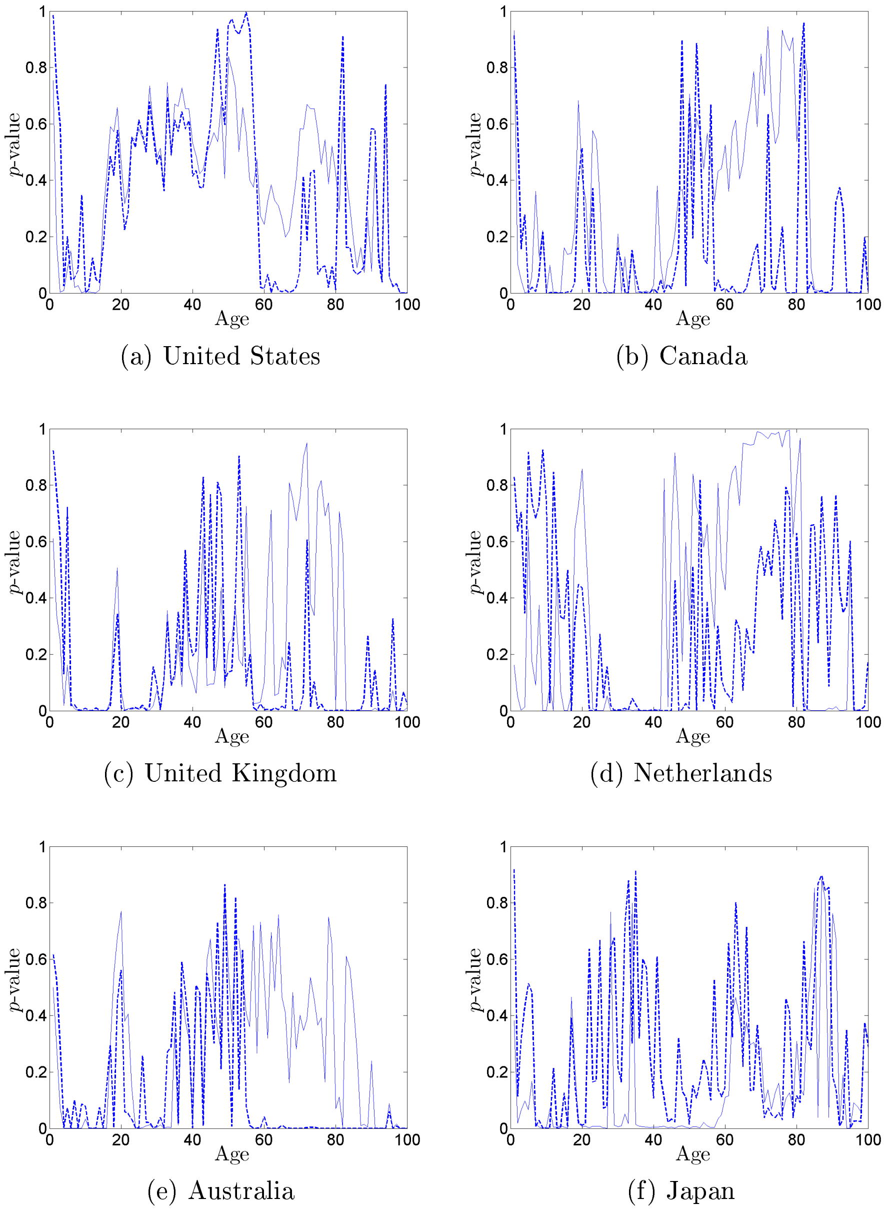


(a) United States (b) Canada

(c) United Kingdom (d) Netherlands

(e) Australia (f) Japan

Figure 5.5: p-values of cointegration tests between $\ln(m_{x,t})$ and g_t (solid line), and between $\ln(m_{x,t})$ and κ_t (dashed line) at each age (Females, 1950–2007)



(a) United States (b) Canada

(c) United Kingdom (d) Netherlands

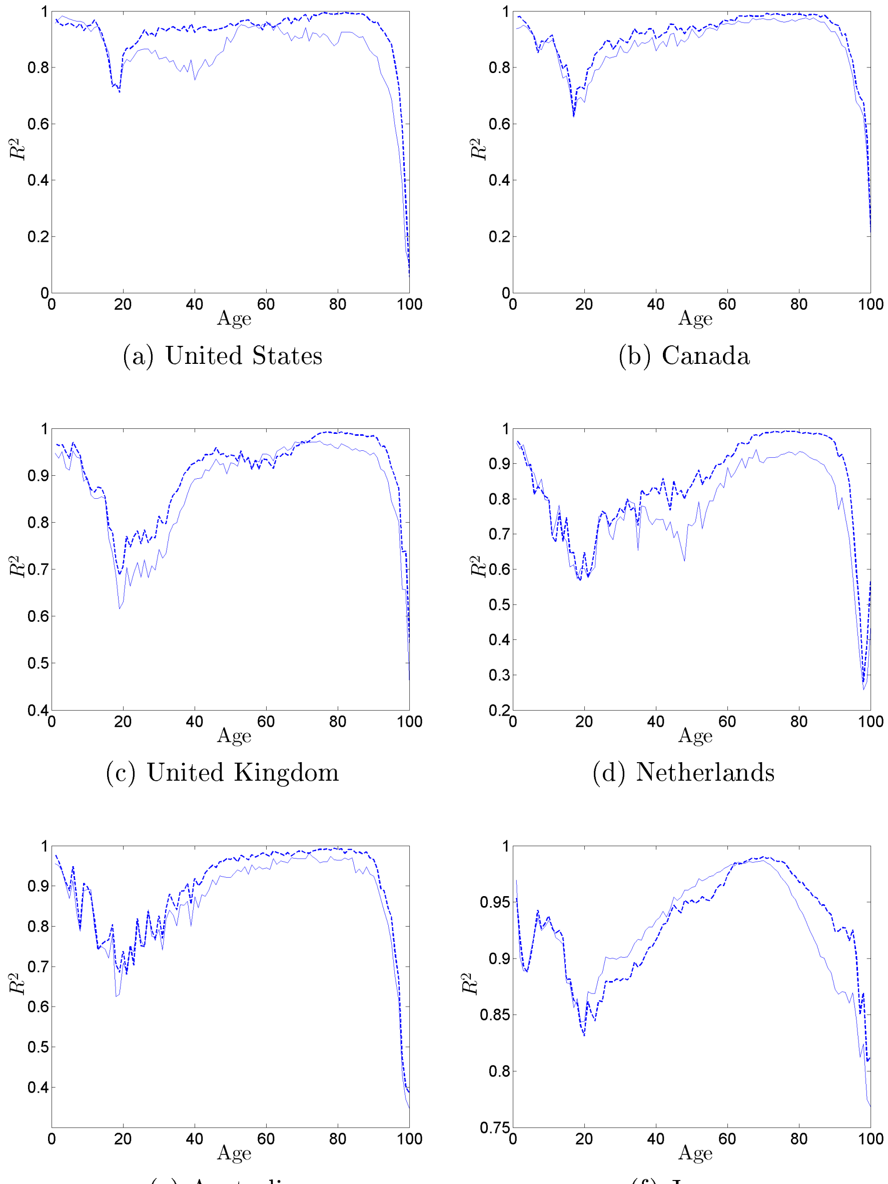
(e) Australia (f) Japan

Figure 5.6: p-values of cointegration tests between $\ln(m_{x,t})$ and κ_t (solid line), and between $\ln(m_{x,t})$ and g_t (dashed line) at each age(Males, 1950–2007)

and United Kingdom males. Roughly speaking, the κ_t-s have sightly higher R^2-s compared to real GDP per capita. However, as κ_t is a latent factor and is estimated, the Lee-Carter model has a much higher degree of freedom, which contributes to its slightly better fit. Moreover, the age-country patterns of R^2-s from κ_t and g_t are quite similar. One exception might be the case for males in the Netherlands, where κ_t has better goodness-of-fit at old ages and g_t is better at very young ages. In general, real GDP per capita can also explain quite a large part of the variations in the mortality rates.

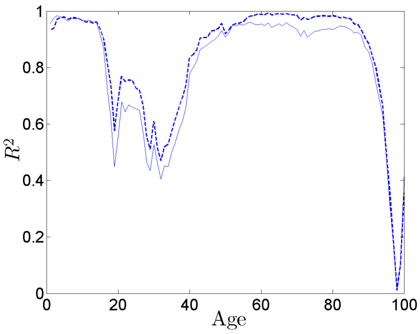
5.9 Additional results for males

As we focus on females in the main text, this section discusses some similar results for males. The patterns of parameters of model (6) for males, shown in Fig. 5.10, are comparable to the patterns for females. Real GDP captures the main time effects. Finally, Fig. 5.11 compares the forecast results from our model and the results from the Lee-Carter model. Compared to the results for females, the forecasted average life-expectancy for males is approximately five years less.

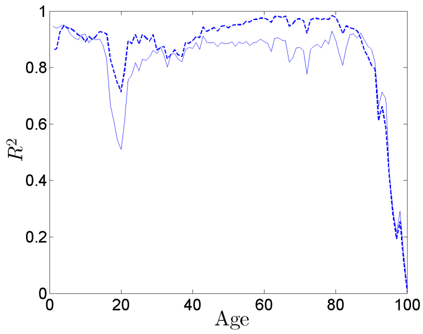


(a) United States
(b) Canada
(c) United Kingdom
(d) Netherlands
(e) Australia
(f) Japan

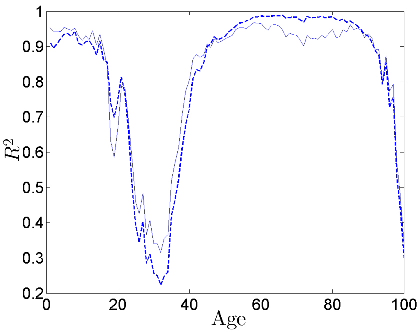
Figure 5.7: R^2 of regressing $\ln(m_{x,t})$ on g_t (solid line) and $\ln(m_{x,t})$ on $\hat{\kappa}_t$ (dashed line) (Females, 1950–2007)



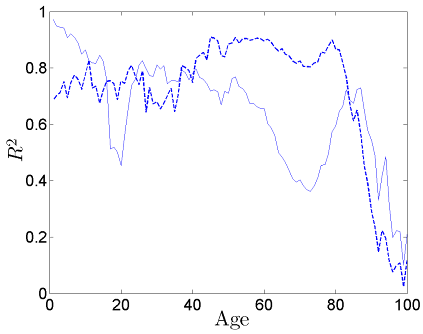
(a) United States



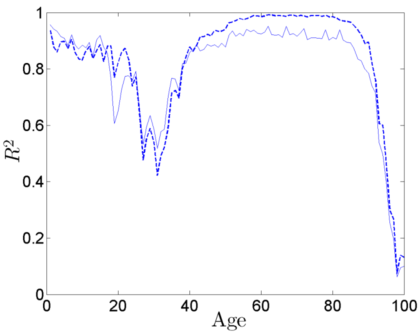
(b) Canada



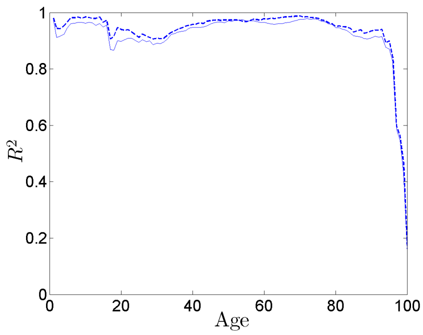
(c) United Kingdom



(d) Netherlands

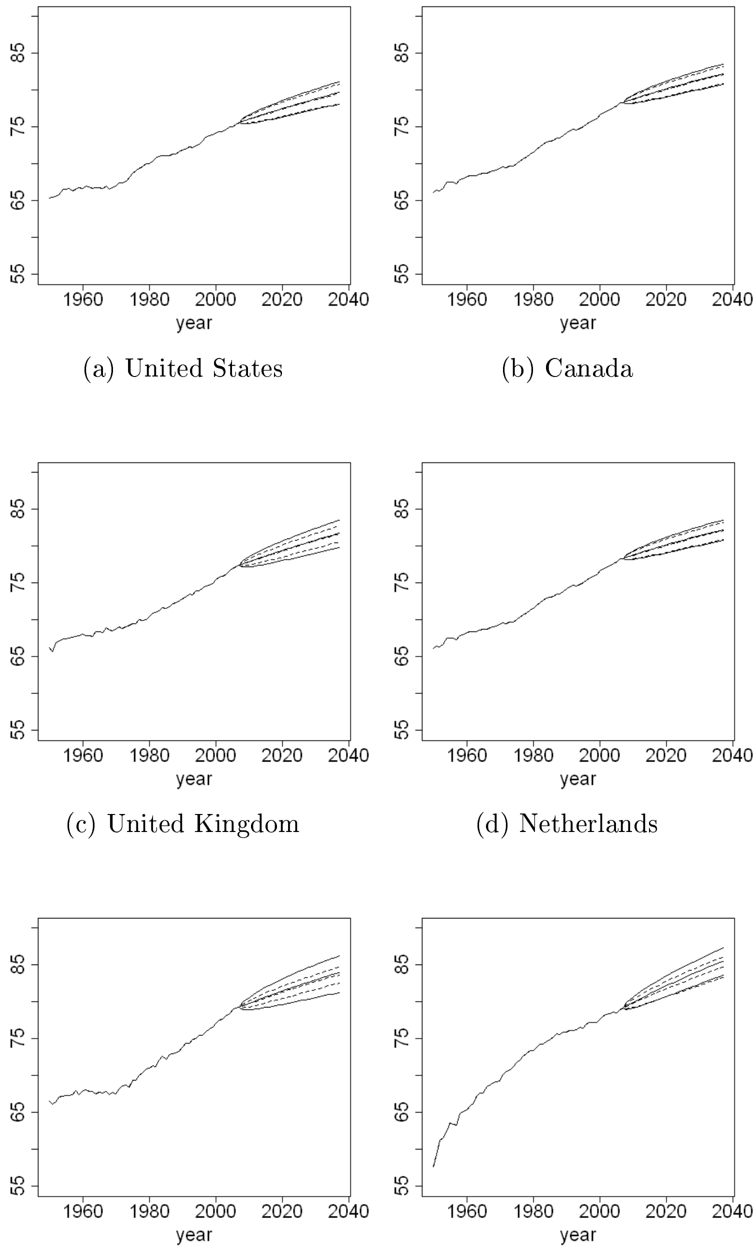


(e) Australia



(f) Japan

Figure 5.8: R^2 of regressing $\ln(m_{x,t})$ on g_t (solid line) and $\ln(m_{x,t})$ on $\hat{\kappa}_t$ (dashed line) (Males, 1950–2007)

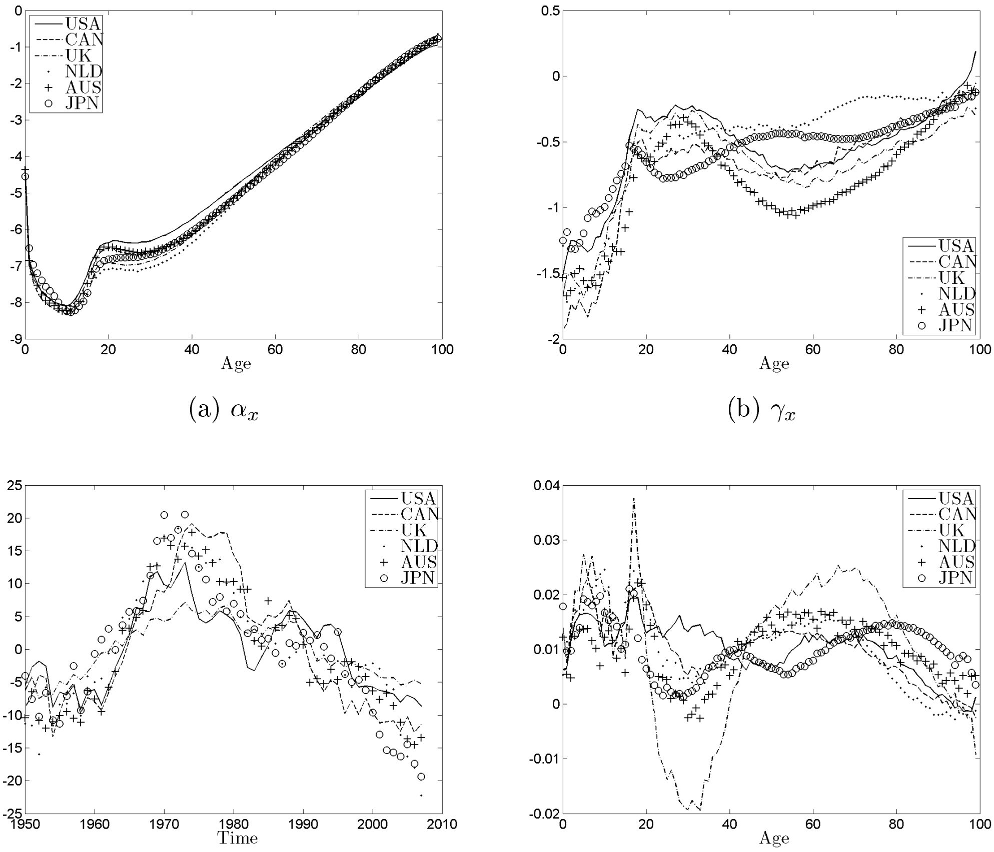


(a) United States (b) Canada

(c) United Kingdom (d) Netherlands

(e) Australia (f) Japan

Figure 5.9: Historical and forecasted life expectancy at birth (e_0),with 95% intervals included (Males). Solid lines represent the results from the Lee-Carter model (1) and dashed lines from model (4)



(a) α_x

(b) γ_x

(c) κ_t

(d) β_x

Figure 5.10: Parameters of model (6) (Males)

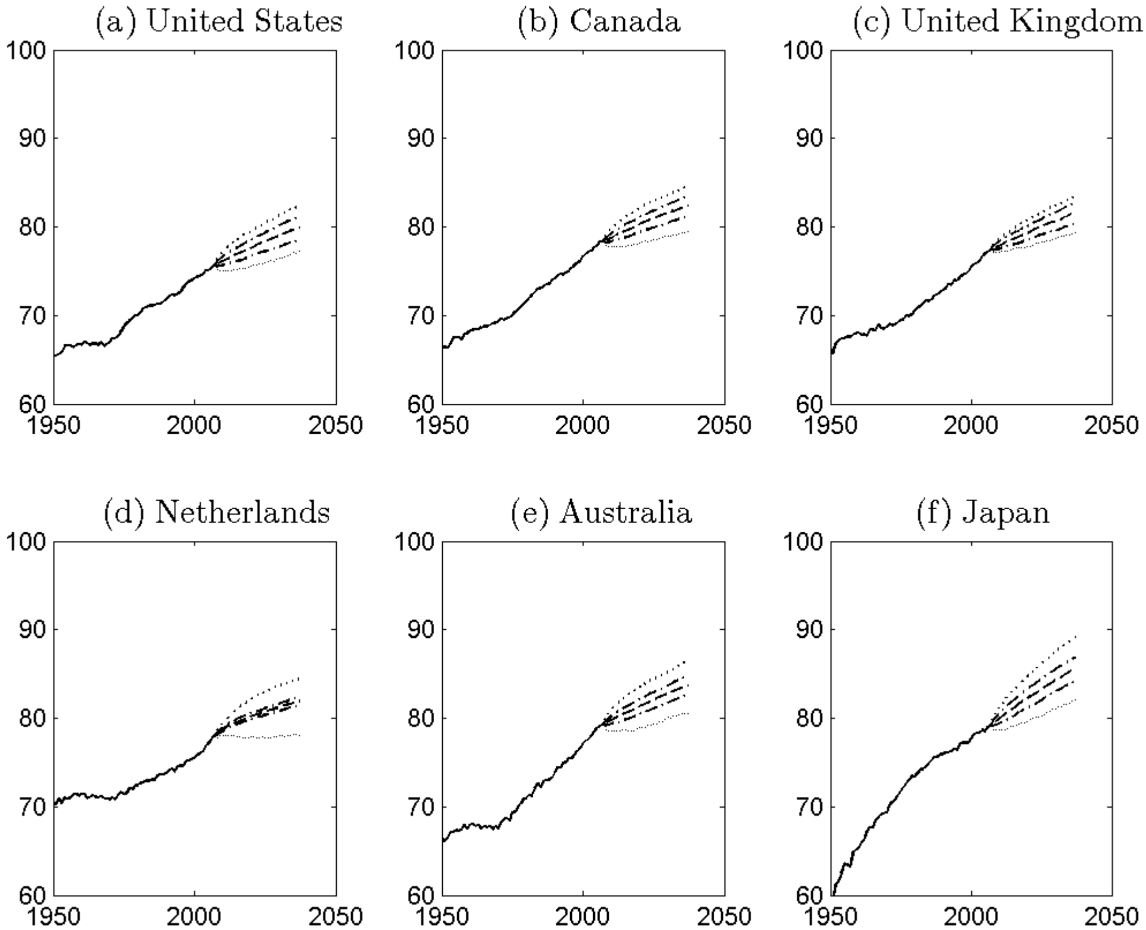


Figure 5.11: Historical and forecasted life expectancy at birth (e_0),with 95% intervals included (Males). Solid lines represent the historical data, dashed lines the forecasted mean values from model (6), dash-dotted lines the 95% bounds including only the variations in g_t, and dotted lines the 95% bounds including the variations in both g_t and κ_t.

Bibliography

Acemoglu, D., & Johnson, S. (2007). Disease and development: The effect of life expectancy on economic growth. *Journal of Political Economy*, *115*, 925–985.

Ahn, S. K., & Reinsel, G. C. (1990). Estimation for partially nonstationary multivariate autoregressive models. *Journal of the American Statistical Association*, *85*, 813–823.

Amromin, G., & Sharpe, S. A. (2013). From the horse's mouth: Economic conditions and investor expectations of risk and return. *Management Science*.

Arcidiacono, P., Hotz, J., & Kang, S. (2012). Modeling college major choices using elicited measures of expectations and counterfactuals. *Journal of Econometrics*, *166*, 3–16.

Armantier, O., Bruine de Bruin, W., Potter, S., Topa, G., van der Klaauw, W., & Zafar, B. (2013). Measuring inflation expectations. *Annual Review of Economics*, *5*, 273–301.

Bellemare, C., Bissonnette, L., & Kröger, S. (2012). Flexible approximation of subjective expectations using probability questions. *Journal of Business & Economic Statistics*, *30*, 124–131.

Beshears, J., Choi, J., Fuster, A., Laibson, D., & Madrian, B. (2013). What goes up must come down? Experimental evidence on intuitive forecasting. *American Economic Review*, *103*, 570–74.

Bhargava, A., Jamison, D. T., Lau, L. J., & Murray, C. J. L. (2001). Modeling the effects of health on economic growth. *Journal of Health Economics*, *20*, 423–440.

Birchenall, J. (2007). Economic development and the escape from high mortality. *World Development*, *35*, 543–568.

Bissonnette, L., & Van Soest, A. (2012). The future of retirement and the pension system: How the public's expectations vary over time and across socio-economic groups. *IZA Journal of European Labor Studies*, *1*, 1–21.

Bloom, D. E., Canning, D., & Sevilla, J. (2004). The effect of health on economic growth: a production function approach. *World Development*, *32*, 1–13.

Booth, H., Maindonald, J., & Smith, L. (2002). Applying Lee-Carter under conditions of variable mortality decline. *Population Studies*, *56*, 325–336.

Booth, H., & Tickle, L. (2008). Mortality modelling and forecasting: A review of methods. *Annals of Actuarial Science*, *3*, 3–43.

Brenner, M. H. (2005). Commentary: Economic growth is the basis of mortality rate decline in the 20th century: Experience of the United States 1901-2000. *International Journal of Epidemiology*, *34*, 1214–1221.

Bresser, D. J., & van Soest, A. (2013). Retirement expectations and satisfaction with retirement provisions. *Review of Income and Wealth*, *forthcoming*.

Brouhns, N., Denuit, M., & Vermunt, J. K. (2002). A Poisson log-bilinear regression approach to the construction of projected lifetables. *Insurance: Mathematics and Economics*, *31*, 373–393.

Browning, M., Gørtz, M., & Leth-Petersen, S. (2013). Housing wealth and consumption: a micro panel study. *The Economic Journal*, *123*, 401–428.

Bruine de Bruin, W., & Manski, C. (2011). Measuring consumer uncertainty about future inflation. *Journal of Applied Econometrics*, *478*, 454–478.

Cairns, A. J. G., Blake, D., & Dowd, K. (2006). A two-factor model for stochastic mortality with parameter uncertainty: Theory and calibration. *Journal of Risk and Insurance*, *73*, 687–718.

Campbell, J., & Cocco, J. (2007). How do house prices affect consumption? evidence from micro data. *Journal of Monetary Economics*, *54*, 591–621.

Carroll, C. (2003). Macroeconomic expectations of households and professional forecasters. *the Quarterly Journal of economics*, *118*, 269–298.

Carroll, C., Otsuka, M., & Slacalek, J. (2011). How large are housing and financial wealth effects? A new approach. *Journal of Money, Credit and Banking*, *43*, 55–79.

Case, K., & Shiller, R. (1988). The behavior of home buyers in boom and post-boom markets. *New England Economic Review*, *November-December*, 29–46.

Case, K., & Shiller, R. (2003). Is there a bubble in the housing market? *Brookings Papers on Economic Activity*, *2003*, 299–362.

Case, K., Shiller, R., & Thompson, A. (2012). What have they been thinking?: Homebuyer behavior in hot and cold markets. *Brookings Papers on Economic Activity*, *2012*, 265–315.

Clapp, J., & Giaccotto, C. (1994). The influence of economic variables on local house price dynamics. *Journal of Urban Economics*, *36*(2), 161–183.

Cocco, J. a. (2004). Portfolio Choice in the Presence of Housing. *Review of Financial Studies*, *18*, 535–567.

Currie, I. D., Durban, M., & Eilers, P. H. C. (2004). Smoothing and forecasting mortality rates. *Statistical Modelling*, *4*, 279–298.

De Bresser, J., & van Soest, A. (2013). Survey response in probabilistic questions and its impact on inference. *Journal of Economic Behavior & Organization*, *96*, 65–84.

De la Croix, D., & Licandro, O. (1999). Life expectancy and endogenous growth. *Economics Letters*, *65*, 255–263.

Delavande, A. (2008). Pill, patch, or shot? Subjective expectations and birth control choice. *International Economic Review*, *49*, 999–1042.

Delavande, A., & Rohwedder, S. (2008). Eliciting subjective probabilities in Internet surveys. *Public Opinion Quarterly*, *72*, 866–891.

Dickey, D., & Fuller, W. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, *74*, 427–431.

DiPasquale, D., & Somerville, C. (1995). Do house price indices based on transacting units represent the entire stock? Evidence from the American housing survey. *Journal of Housing Economics*, *4*, 195–229.

Doepke, J., Dovern, J., Fritsche, U., & Slacalek, J. (2008). The dynamics of European inflation expectations. *BE Journal of Macroeconomics*, *8*, 1–21.

Dominitz, J. (1998). Earnings expectations, revisions, and realizations. *Review of Economics and Statistics*, *80*, 374–388.

Dominitz, J. (2001). Estimation of income expectations models using expectations and realization data. *Journal of Econometrics*, *102*, 165–195.

Dominitz, J., & Manski, C. (1997a). Perceptions of Economic Insecurity: Evidence from the Survey of Economic Expectations. *Public Opinion Quarterly*, *61*, 261–287.

Dominitz, J., & Manski, C. (1997b). Using expectations data to study subjective income expectations. *Journal of the American Statistical Association*, *92*, 855–867.

Dominitz, J., & Manski, C. (2004). How should we measure consumer confidence? *Journal of Economic Perspectives*, *18*, 51–66.

Dominitz, J., & Manski, C. (2007). Expected equity returns and portfolio choice: Evidence from the Health and Retirement Study. *Journal of the European Economic Association*, *5*, 369–379.

Dominitz, J., & Manski, C. (2011). Measuring and interpreting expectations of equity returns. *Journal of Applied Econometrics*, *26*, 352–370.

Dovern, J., Fritsche, U., & Slacalek, J. (2012). Disagreement among forecasters in G7 countries. *Review of Economics and Statistics*, *94*, 1081–1096.

Dräger, L., & Lamla, M. J. (2012). Updating inflation expectations: Evidence from micro-data. *Economics Letters*, *117*, 807–810.

Duca, J., Muellbauer, J., & Murphy, A. (2011). House prices and credit constraints: Making sense of the us experience. *The Economic Journal*, *121*, 533–551.

Easaw, J., Golinelli, R., & Malgarini, M. (2013). What determines households inflation expectations? Theory and evidence from a household survey. *European Economic Review*, *61*, 1–13.

Easaw, J., & Roberto, G. (2010). Households forming inflation expectations: Active and passive absorption rates. *The BE Journal of Macroeconomics*, *10*, 1–32.

Elliott, G., Rothenberg, T., & Stock, J. (1996). Efficient tests for an autoregressive unit root. *Econometrica*, *64*, 813–836.

Engle, R. F., & Granger, C. W. J. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica*, 251–276.

Ettner, S. L. (1996). New evidence on the relationship between income and health. *Journal of Health Economics*, *15*, 67–85.

Favara, G., & Song, Z. (2014). House price dynamics with dispersed information. *Journal of Economic Theory*, *149*, 350–382.

Gao, A., Lin, Z., & Na, C. (2009). Housing market dynamics: Evidence of mean reversion and downward rigidity. *Journal of Housing Economics*, *18*, 256–266.

Hall, A., Anderson, H., & Granger, C. (1992). A cointegration analysis of treasury bill yields. *Review of Economics and Statistics*, 116–126.

Han, L. (2010). The effects of price risk on housing demand: Empirical evidence from us markets. *Review of Financial Studies*, *23*, 3889–3928.

Hanewald, K. (2011). Explaining mortality dynamics: the role of macroeconomic fluctuations and cause of death trends. *North American Actuarial Journal*, *15*, 290–314.

Hauck, K., & Rice, N. (2004). A longitudinal analysis of mental health mobility in Britain. *Health Economics*, *13*, 981–1001.

Head, A., & Lloyd-Ellis, H. (2012). Housing liquidity, mobility, and the labour market. *Review of Economic Studies*, *79*, 1559–1589.

Hoffmann, A. O., & Post, T. (2013). How return and risk experiences shape investor beliefs and preferences. *Available at SSRN 1970284*.

Hudomiet, P., Kézdi, G., & Willis, R. (2011). Stock market crash and expectations of American households. *Journal of Applied Econometrics*, *26*, 393–415.

Hurd, M. (2009). Subjective Probabilities in Household Surveys. *Annual Review of Economics*, *1*, 543–562.

Hurd, M., & McGarry, K. (1995). Evaluation of the subjective probabilities of survival in the Health and Retirement Study. *Journal of Human Resources*, *30*, S268–S292.

Hurd, M., & Rohwedder, S. (2011). *Effects of the financial crisis and Great Recession on American households* (Tech. Rep.). National Bureau of Economic Research.

Hurd, M., van Rooij, M., & Winter, J. (2011a). Stock market expectations of Dutch households. *Journal of Applied Econometrics*, *26*, 416–436.

Hurd, M., van Rooij, M., & Winter, J. (2011b). Stock market expectations of Dutch households. *Journal of Applied Econometrics*, *26*, 416–436.

Iacoviello, M., & Pavan, M. (2013). Housing and debt over the life cycle and over the business cycle. *Journal of Monetary Economics*, *60*, 221–238.

Jacobsen, B., Lee, J., Marquering, W., & Zhang, C. (2014). Gender differences in optimism and asset allocation. *Journal of Economic Behavior & Organization*, *forthcoming*.

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, *12*, 231–254.

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in gaussian vector autoregressive models. *Econometrica*, 1551–1580.

Johansen, S. (1992). Determination of cointegration rank in the presence of a linear trend. *Oxford Bulletin of Economics and Statistics*, *54*, 383–397.

Kaplanski, G., Levy, H., Veld, C., & Veld-Merkoulova, Y. (2013a). Do happy people make optimistic investors? *Journal of Financial and Quantitative Analysis*, *forthcoming*.

Kaplanski, G., Levy, H., Veld, C., & Veld-Merkoulova, Y. (2013b). Do happy people make optimistic investors? *Journal of Financial and Quantitative Analysis*, *forthcoming*.

Kiel, K., & Carson, R. (1990). An examination of systematic differences in the appreciation of individual housing units. *Journal of Real Estate Research*, *5*, 301–318.

Kleibergen, F., & van Dijk, H. (1994). Direct cointegration testing in error correction models. *Journal of Econometrics*, *63*, 61–103.

Kleinjans, K. J., & van Soest, A. (2013). Rounding, focal point answers and nonresponse to subjective probability questions. *Journal of Applied Econometrics*, *29*, 567–585.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root : How sure are we that economic time series have a unit root? *Journal of Econometrics*, *54*, 159–178.

Lee, R. D., & Carter, L. R. (1992). Modeling and forecasting US mortality. *Journal of the American Statistical Association*, *87*, 659–671.

Lee, R. D., & Miller, T. (2001). Evaluating the performance of the Lee-Carter method for forecasting mortality. *Demography*, *38*, 537–549.

Li, W., & Yao, R. (2007). The life-cycle effects of house price changes. *Journal of Money, Credit and Banking*, *39*, 1375–1409.

Lovenheim, M., & Mumford, K. (2013). Do family wealth shocks affect fertility choices? Evidence from the housing market. *Review of Economics and Statistics*, *95*, 464–475.

Malmendier, U., & Nagel, S. (2011). Depression babies: Do Macroeconomic experiences affect risk taking? *The Quarterly Journal of Economics*, *126*, 373–416.

Manski, C. (2004). Measuring expectations. *Econometrica*, *72*, 1329–1376.

Miller, N., Peng, L., & Sklarz, M. (2011). The economic impact of anticipated house price changes: Evidence from home sales. *Real Estate Economics*, *39*, 345–378.

Nagel, S. (2012). Macroeconomic experiences and expectations: A perspective on the Great Recession. *Working paper*.

Nandi, A., Prescott, M. R., Cerdá, M., Vlahov, D., Tardiff, K. J., & Galea, S. (2012). Economic conditions and suicide rates in New York city. *American Journal of Epidemiology*, *175*, 527–535.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, *49*, 1417–1426.

Nielsen, B., & Nielsen, J. (2010). Identification and forecasting in the Lee-Carter model. *Working Paper*.

Oh, W., & Lee, K. (2004). Causal relationship between energy consumption and GDP revisited: the case of Korea 1970–1999. *Energy economics*, *26*, 51–59.

O'Hare, C., & Li, Y. (2012). Explaining young mortality. *Insurance: Mathematics and Economics*, *50*, 12–25.

Pástor, L., & Stambaugh, R. F. (2012). Are stocks really less volatile in the long run? *The Journal of Finance*, *67*, 431–478.

Peng, L., & Thibodeau, T. (2013). Risk segmentation of American homes: Evidence from Denver. *Real Estate Economics*, *41*, 569–599.

Perron, P. (1988). Trends and random walks in macroeconomic time series: Further evidence from a new approach. *Journal of Economic Dynamics and Control*, *12*, 297–332.

Pfajfar, D., & Santoro, E. (2013). News on inflation and the epidemiology of inflation expectations. *Journal of Money, Credit and Banking*, *45*, 1045–1067.

Phillips, P., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, *75*, 335–346.

Piazzesi, M., & Schneider, M. (2009). Momentum traders in the housing market: Survey evidence and a search model. *American Economic Review*, *99*, 406–411.

Pitacco, E., Denuit, M., Haberman, S., & Olivieri, A. (2009). *Modelling Longevity Dynamics for Pensions and Annuity Business (Mathematics Texts).* Oxford University Press.

Plat, R. (2009). On stochastic mortality modeling. *Insurance: Mathematics and Economics*, *45*, 393–404.

Pollakowski, H., Stegman, M., & Rohe, W. (1991). Rates of return on housing of low-and moderate-income owners. *Real Estate Economics*, *19*, 417–425.

Pritchett, L., & Summers, L. H. (1996). Wealthier is healthier. *Journal of Human Resources*, 841–868.

Seward, A., Delaney, C., & Smith, M. (1992). An empirical analysis of housing price appreciation in a market stratified by size and value of the housing stock. *Journal of Real Estate Research*, *7*, 195–205.

Souleles, N. (2004). Expectations, heterogeneous forecast errors, and consumption: Micro evidence from the Michigan consumer sentiment surveys. *Journal of Money, Credit, and Banking*, *36*, 39–72.

Soytas, U., & Sari, R. (2003). Energy consumption and GDP: causality relationship in G-7 countries and emerging markets. *Energy economics*, *25*, 33–37.

Stephens Jr, M. (2004). Job loss expectations, realizations, and household consumption behavior. *Review of Economics and Statistics*, *86*, 253–269.

Swift, R. (2011). The relationship between health and GDP in OECD countries in the very long run. *Health Economics*, *20*, 306–322.

Van der Klaauw, W. (2012). On the use of expectations data in estimating structural dynamic choice models. *Journal of Labor Economics*, *30*, 521–554.

Wilmoth, J. R. (1993). *Computational methods for fitting and extrapolating the lee-carter model of mortality change* (Tech. Rep.). Technical report, Department of Demography, University of California, Berkeley.

Yao, R. (2004). Optimal Consumption and Portfolio Choices with Risky Housing and Borrowing Constraints. *Review of Financial Studies*, *18*, 197–239.

Zhang, J. (2013). House price expectations: Unbiasedness and efficiency of forecasters.